# Big Data Credit Scoring in China: Organisation of Work, State Aspiration and Impact on Financial Inclusion

by

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# Table of contents

# List of tables and illustrated materials

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# Author’s declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. I hereby declare that I am the author of the thesis, that the work of which this thesis is a record has been carried out by myself, that no material contained in the thesis has been used before or published and that this thesis has not been submitted in any previous application for any degree at another university.

[redacted]

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# Summary

This thesis examines the configuration of Big Data algorithmic credit scoring. It is situated within the context of the Chinese government's programme to construct a social credit system. Based on ethnographic fieldwork in a credit modelling team of a major internet company in China, the findings of this thesis provide organisational-level evidence regarding the various critical factors influencing the design, modelling, usability and outcome of the configuration of credit models. The three empirical chapters respectively reveal the organisation of data science work, organisational innovation of technology in delivering on state aspirations and the societal consequences of the Big Data driven quantification of creditworthiness. The thesis contributes to the literature on technological affordance, governmentality literature on calculative technology, and to literature on calculative cultures by offering a rich empirical analysis of algorithmic credit scoring in China. The findings are of interest to scholars researching the future of work, the production of algorithmic measures and the socio-economic impacts of calculative devices. The findings should also be of practical interest to organisations building data science teams, to policy makers designing state calculaive programmes and to parties concerned about the impact of algorithmic decision making on financial inclusion.

# List of abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| CDRC | China Development and Reform Commission |
| CPU | Central Processing Unit |
| CSC | Credit Scoring Centre |
| ETL | Extract, Transform and Load (data) |
| FIB | Financial Innovation Branch |
| GDP | Gross Domestic Product |
| ID | Identification |
| IT | Information Technology |
| IV | Information Value |
| KPI | Key Performance Indicator |
| KS | Kolmogorov-Smirnov test |
| ML | Machine Learning |
| NIFA | National Internet Finance Association of China |
| OS | Operation System |
| PBoC | People’s Bank of China |
| P2P | Peer to Peer Lending |
| RegTech | Regulatory Technology |
| XGB | XGBoost |

# I. Introduction

## 1. Setting the scene: in the age of data analytics and algorithmic measures

The progressive use of computational technology aims to replace not only the bodily functions (Marx, 1887/1975) of manual work but also to extend human intelligence with data-driven insights. Data analytics, i.e. a set of technologies to process, transform and model data, is increasingly being used to inform and support decision-making in various domains. Expanding on the 'smart machine' of information processing (Joerges, 1989; Zuboff, 1984), the pervasive use of data analytics has led to 'datafication' of consumers' digital traits in all realms of life (Alaimo and Kallinikos, 2017). Data analytics intensifies the use of personal data for targeted marketing campaigns, providing tailored daily services, self-tracking programs, risk management, pricing mechanisms, credit scoring, and other economic scenarios.

Moreover, algorithms are being deployed to quantify Big Data, producing an ever-increasing number of quantitative measures (Mennicken and Espeland, 2019) that are often invisible to individuals (Beer, 2015; Pasquale, 2015). Specifically, artificial intelligence and machine learning models have in recent years taken centre stage. Proprietary algorithms with the integration of these models are being configured to make assessments of individuals. By creating behavioural classifications (Mayer-Schonberger and Cukier, 2013) and digital depictions of consumers' abstract forms (Fourcade and Healy, 2013), these algorithms can impact individuals' life choices and opportunities (O'Neil, 2016), as well as create structural stratification (Fourcade and Healy, 2017). These developments further trigger 'reactivity' and re-direct human behaviours through inviting a form of reflexivity (Espeland and Sauder, 2007).

Meanwhile, the implementation of these technologies is currently modifying organisational work processes (Constantiou and Kallinikos, 2014; Orlikowski and Scott, 2015; Zammuto et al., 2007). To take advantage of this paradigm of big data, managers need new opportunities for organising work and new strategies to envision and implement what the technology allows them to do. Given the integration of more analytical functions (Mikes, 2009) and the use of different models and algorithms (Svetlova and Dirksen, 2014), how does the integration of these technological features affect work processes? Are we on our way to witnessing a new future for work? Do computational machines also play a major role in reconfiguring the work performed by skilled cognitive workers? These questions underpin the present thesis.

In addition to allowing for new opportunities for the organisation of work, big data and algorithmic quantitative measures also enable new opportunities for social governance (Dunleavy et al., 2006). Previous research has found quantitative measures to be important embodiments for devising governance (Davis et al., 2012; Mehrpouya and Samiolo, 2016; Rottenburg et al., 2015) and denoting trust (Jeacle and Carter, 2011). How then is the promise of science and technology mobilised in terms of new forms of governance? Who are the actors and what are the mechanisms affecting the production of these big data algorithmic measures?

Algorithmic measures permeate daily life and bring forth socio-political impacts that are gradually becoming manifest (Fourcade and Healy, 2013, 2016; Lazer and Radford, 2017; Zuboff, 2019). Zuboff (2019) points out that ‘the digital can take many forms depending upon the social and economic logics that bring it to life’ (p. 20). What are the social and economic elements affecting the production of algorithms and by that, also their outcomes? How do these technologies affect the life choices and opportunities of individuals? Can algorithmic measures ensure fairness and avoid structural injustice?

As researchers (Mayer-Schonberger and Cukier, 2013; Hu, 2020; Obar, 2020) have repeatedly expressed concerns about the 'black box society' (Pasquale, 2015), this thesis (consisting of three papers) is positioned on the stage of these technological advancements and concerns with the relevant questions presented in the above three paragraphs within this broad area. This thesis is motivated to offer a timely assessment of how these 'new forms of quantification' (Mennicken and Espeland, 2019, p.224) are being arranged, calculated and produced with the use of data analytics and algorithms.

## 2. Context

### 2.1 Why credit scoring and why China?

> 'A technological platform for common calculation can be the carrier of profound political displacement and of astounding economic change' (Poon, 2009, p. 670).

This doctoral thesis studies the empirical phenomenon of credit scoring in China. This study is set in the context of the Chinese government's programme to construct a social credit system. The phenomenon encompasses a set of technological configurations, underlying social changes and a technology of political governance. This programme prompts the need for research on the organisation of work, social governance and social changes made possible by this new form of technology.

Credit scoring is a critical technology in determining whom lenders extend credit to, and whom they do not. Its quantification manifests a concept of creditworthiness to indicate 'how much money that one can repay and how much money one can get' (Marron, 2007). The attention paid to credit scoring by this thesis is motivated by the recent forms it has taken in China to scrutinise citizens' multidimensional social behaviours, examining their financial, educational, web browsing and other personal social data to evaluate lending risk. This new credit technology deepens its implantation into consumer's' life and brings with it a closer scrutiny of personal data.

The emergence of this technology takes place alongside Chinese credit expansion, which has led the Chinese state to seek effective technology for risk management. China has been encouraging a socio-economic transition from a saving-led economy to a debt-fuelled credit society in recent years (Xinhua, 2016). The Chinese government is moving its attention to the creation and use of credit to boost the economy (Ding, 2015) and its growth has become more increasingly dependent on domestic consumption.

The demand for credit scoring arises from the need to develop a solution for unreliable and untrustworthy conduct that has been experienced during the growth of internet finance. Threats to the economy materialised in 2014 and 2015, when a large quantity of online debtors escaped repayments (People's Bank of China, 2015). This drew the government's attention (People's Bank of China, 2015), who subsequently expressed the need for a 'trustworthy and sincere society' where citizens will be reliable, trustworthy and fulfil his or her promises and economic contracts (The Chinese State Council, 2014, 2016). The same priority was also addressed in the 13th Five-year development plan (The Chinese State Council, 2016).

To accelerate information collection from consumers and to create an effective algorithmic model to measure creditworthiness, the People's Bank of China (PBoC) appointed eight Chinese companies to utilise online data and algorithmic scoring methods to calculate personal credit scores for the entire population of China. Selected as state-approved pilot projects, these eight companies possessed different capabilities in complementing the data gaps in the nationwide centralised database of personal data and algorithmic modelling. After receiving the notice from PBoC to start conducting personal credit reporting (PBoC, 2015), these companies started establishing practices for credit scoring. Standing at different starting points, these companies applied different understandings of creditworthiness and used different sets of data for credit scoring.

## 2.2 The Notion of Credit and Debt and the Development of Credit Agencies

While credit scoring has adapted into its new forms, the notion of debt and credit is much older, and occurred before the arrival of money (Graeber, 2011). For example, fiat money, China's paper currency, first emerged from expanding the use of credit instruments that were created in the context of daily economic transactions, i.e. not initially created by a government (Graeber, 2011). This section offers a general background of credit and debt to understand the concepts underpinning them and positions this study in the broad history of the development of credit rating agencies.

Graeber (2011) sees credit and debt in relational terms, i.e. the relationship between creditor and debtor. He makes a comparison to everyday market transactions, where shops or stalls make transactions based on cash and coin. This facilitates transactions between strangers and a degree of anonymity. Conversely, credit occurs based on informed relationships. However, Graeber also points out that this relationship is rarely if ever power neutral, as he shows that debt is preserved by systematic state violence in favour of creditors (2011). He explains that, although credit and debt have had economic imaginaries attached to them as moral obligations, they have long been maintained by violence. He explains that credit and debt have long been interwoven with forms of violence, and developed later, alongside the development of international politics and the political economy of today.

Graeber (2011) uses examples such as blood-feuds, slave trading and gangsters to make the point that debt is often underpinned by violence. For example, violence has been used to repay blood-feuds, forcing people into further debt, or even to repay debts with continual slavery, particularly when ancient forms of human economies are considered, where money was a social currency serving to maintain relations between people rather than to purchase things. Even with the rise of Roman law, Graeber (2011) argues that there is no intrinsic difference between ‘private property and political power – at least, insofar as that power was based in violence’ (p. 204). The violence is preserved within the structure of the law, ensuring that morality turns out to be, above all, a matter of paying one's debts.

Debt is seen as an obligation. Thus, it is historically overlaid with a moral frame of reference. As can be seen in the bible and other religious texts, life is viewed as a debt to God and the religious terms ‘debt of honor and honoring one’s debt’ are understood as obligations (Graeber, 2011, p. 166). However, these concepts of morality were not diminished with the development of the global institutions of market economies. Even today, power is not balanced between debtor and creditor. In Graeber’s words, ‘the new age of credit money we are in seems to have started precisely backwards. It began with the creation of global institutions like the IMF designed to protect not debtors, but creditors.’ (2011, p. 18). Graeber (2011) points out that the current social order, rules and institutions have been set up to protect creditors, instead of debtors.

The emergence of credit ratings needs to be understood in this context. With the growing need for doing business with strangers and the rise of credit instalments in 1841 (Lynn, 1957; Carruthers and Ariovich, 2010), a number of companies in the US began to systematically collect and process information about the creditworthiness of other firms. With the aim of helping to make lending uncertainties more traceable, information processing took place as a response to the question of how to manage credit, which was made urgent due to the financial crisis of 1837 (Carruthers, 2013).

In this early form of credit rating, classification was used to turn distinctive uncertainties into calculable risks and place the information in a quantitative form. credit agencies placed companies into different categories and then to determine their according frequency of default (Guseva and Rona-Tas, 2001). Through developing a standardised ordinal category system into which firms were classified, rating agencies recognised risk through classification (Carruthers, 2013). The classifications included factors such as basic credit rating as the main method to help analyse a large volume of mixed information in inconsistent formats about firms. According to March and Simon (1958), at that time, classification helped to assimilate uncertainty.

These rating agencies sold information in the form of credit reports and credit ratings to an ever increasing number of clients, such as insurance and banking professionals. In addition, the rating agencies also produced a reference book in which they list rated companies alphabetically for subscribers to seek information about their client companies for reference and evaluation. However, due to a lack of accuracy of these ratings, they were subject to various conflicts and legal challenges (Cohen, 2012), as debtor companies who used the ratings to select companies to lend to subsequently failed to pay.

However, the use of credit ratings was integrated into regulations in the 1930s, and they became enforceable by the state. Since then, credit rating has expanded to serve various forms of financial products across different levels and industries. In the early 20th century, with the development of financial markets where the use of derivatives grew (Cantor and Packer, 1994), the use of credit ratings expanded from short-term trade credit markets to those relating to long-term corporate borrowing. Developing beyond categorisation, Moody's uses its own quantitative evidence about default performance, and a statistical measure is used to calculate default rates (Fons, 2004). The probability of default has been calculated to the extent that Moody's attaches evidence of default to its ratings.

To date, credit ratings reports have been integrated into financial institutions as part of best practice. Credit rating is used to guide the allocation of a wide range of credit related activities, such as trade credit, consumer credit, mortgage credit, small business credit, corporate credit and even governance of sovereign credit (Poon, 2009; Poon, 2007; Coffee, 2006; Akhavein et al., 2005; Sinclair, 2005). However, risk can be calculable, whereas uncertainty can not (Knight, 1971). The limitations of credit rating were exposed in the financial crisis of 2008, and retrospective critiques of credit rating were demonstrated by its evaluation as a form of bilateral relationship, which had become overlooked in the complex networks of financial markets.

Following the development of credit rating agencies, ways of quantifying risk have used updated methods. Following on from categorisation, credit control has developed from screening to control by the predictions of risk (Poon, 2009); credit rating agencies set up models for calculations of future default rates. With the preference of quantitative analytics (Mikes, 2011), credit scoring has turned to the escalated use of big data and analytics, although empirical research capturing the ‘big data turn’ in credit rating is very sparse. The present study seeks to fill this lacuna.

### 2.3 The Genealogy of socio-economic governance in China

Governance is not merely the domain of public policy, but a way to construct the ideal citizen. Miller and Rose (2006) have demonstrated that the indirect technology of governing aligns economic, social and personal conduct with socio-political objectives from a distance (Latour, 1987). Likewise, previous studies on Chinese post-socialist reforms have drawn attention to governing technologies, such as hukou and danwei (meaning *registry* and *unit* in Chinese) (Bray, 2005; Zhang, 2018), showing that the development of legal and socio-economic frameworks that can restrict one’s mobility later constitute spaces within which one can exercise one’s rights.

Socio-economic governance echoes different government rationalities (Shamir, 2005, p.200), which embody a transformation to a post-socialist neoliberal governance (Gleiss, 2016). This section explores the genealogy of relevant socio-economic governance elements that underpin an individual's life in China, on which this thesis focuses.

Bray (2005) applied Foucault's (1977) genealogical method to understand danwei as he found that the danwei format took on heterogeneous forms of past practices and, into its different formation, layered into what Frazier (2002) called 'a matrix of labour management institutions' (p.72-73). Bray explained that danwei arose from the 'juxtaposition of a wide range of disciplinary, governmental, biotechnical, and spatial practice over a considerable period of time' (p.195), which could be traced back to the Yan'an[1] period (Womack, 1991). It shared many similarities with the traditional style clan (Yang, 1994) of China's past and was influenced by 'practices from the more recent Republican period and from the Soviet Union' (Bray, 2005, p.7). This different, disconnected and dispersive layering replicates Foucault's interwoven form of knowledge that constitutes the discursive power, Foucault's genealogical studies and addresses the technologies of the human bodies to modern power relations.

Bray (Bray, 2005) argues that danwei space was arranged in order to directly promote socialist collectivity. Danwei was a socialist organisational work unit in which individual workers were employed. It was a system set up to solve the organisational and practical problems that occurred in China in the 1940s and 1950s (Lu, 1993). It comprised the elemental units of Chinese cities and was a means to organise the population. Danwei included many different organisations of varying size and type, such as factories, schools, hospitals and stores. Beyond its function as a workplace for its employees, danwei also provided and underpinned welfare services, such as housing, childcare, free medical care and dining halls, as well as being a collective enterprise to employ workers' family members and others. Additionally, danwei covered

[1] (a town where the Communist party was based, from 1935 to 1948)

ideological studies, policing, security, marriage, divorce and entry into the communist party for individuals, which encompassed a wide array of political, judicial, civil and social functions. Given their multi-faceted functions, danweis gradually began to indicate one's social identity and *mianzi*, or face, meaning that an individual without a danwei could be portrayed as 'suspicious' (Bray, 2005, p.5).

Another government policy that exhibits layering is the hukou system. This system requires all citizens to register with their local hukou authority after birth. An individual's access to education and resources is fixed to this registration, and the birth hukou cannot be changed easily, particularly rural-urban migrants to major cities. The establishment of this system began in the 1950s, though registration and classification of the population has ancient roots. Based on the 1958 Regulation on Household Registration, one's hukou is attached to one's birthplace and is assigned and categorised as either agricultural or non-agricultural. It is unlikely that a rural, agricultural resident would be able to change their status to a non-agricultural hukou (Chan, 2009). This act restricted unauthorised migration from rural areas to urban cities and, until the 1970s, limited the possibility of people with an agricultural hukou finding work in the danwei (Bray, 2005).

After the economic reform of 1978, the strict control of citizen mobility was removed. Moreover, the 1985 Regulation on the Management of Temporary Residents in Cities and Towns permitted rural migrants with a temporary residence permit to live in cities for over three months, without having a local hukou. Meanwhile, a points system was introduced in some cities where migrants could accumulate enough points to qualify for a hukou in the city. At this time, the objective was no longer to limit, 'but to govern mobility' (Zhang 2018, p.856). There were concerns and problems regarding social order (known as *shehui zhian*), but in this case, separate from exclusion, the social and spatial hierarchies were maintained through differential inclusion.

With the rationality of the government changing, the focus of technology has adapted. The binary  separation of agricultural and non-agricultural hukou was for the purpose of restricting mobility, due to the unbalanced resources between urban city and rural areas, under Mao's approach of a planned economy. However, the significance of danwei and hukou has been weakened due to the economic reforms introduced to bring about a market economy. Similarly, a government rationality developed that centred on injecting labour from rural areas into the cities. Later with growing societal dissatisfaction with hukou segregation, the increasing salience of rural-urban migrants became a governmental problem. In 2006, the government put together an integration plan for rural-urban migrants. Meanwhile, during the transition to the market economy, some institutions began to replace the role of danwei, such as *shequ* (community), and people were encouraged to run their own businesses.

Consequently, danwei and hukou not only facilitates other governmental projects and economic reform at the macro-level, but also introduces differentiations in all aspects of socio-economic life at the micro-level. Accordingly, individuals' spatial responsibilities and rights are modified in line with the change of government rationality. For instance, hukou and danwei are critical in deciding one's access to social welfare benefits and public services and closely linked to informal discriminations in the labour market, regarding the labour rights and working conditions of migrant workers (Smart and Lin, 2007; Swider, 2016), which rely on calculative practices. Through governmental technologies based on classification and calculation, Wang and Liu (2018) suggested, such system plays a central role in resource allocation and population management, which creates spatial order of citizenship through two interlaced and co-constructive forms of power: 'the state's coercive power and the free operation of market forces' (Zhang, 2018, p. 863).

Along with the changing focus of these perennial policies, the imagination around the 'ideal citizens' was reviewed and updated. The switched focus of hukou and danwei after the economic reform reconfigures the relationship between state and society and reconstructs the subjectivity of citizens into self-responsible, autonomous and entrepreneurial individuals (Bray and

Jefferys, 2016). The increased reliance on market mechanisms draws individuals into the ‘profit motive’ (Dutton and Hindess, 2016, p.18), which requires legal protection of such mechanisms and personal autonomy in contrast to more centralised ways of governing. Moreover, Sigley (2006, p.502) summarises that under such a governance regime, the role of central government is not weakened, but transforms to become more reliant on the legal system and administrative commands. With the emergence of different societal problems, the rationality of governing changes. It is in the context of the proliferation of what is perceived to be dishonest and untrustworthy behaviour, resulting from the ‘profit motive’ after the economic reform, that the social credit system needs to be understood.

## 3. Data collection and the ethnographic field

This thesis employs qualitative methods and analyses data collected from ethnographic fieldwork within a credit modelling team in a Chinese internet company. Data sources include interviews with product managers, model developers, and directors from seven other pilot companies, as well as documents obtained from government archives and official speeches. The author conducted 695 hours of ethnographic fieldwork between May and August of 2018, which enables this thesis to examine technological enactment from the frontline of work and to observe technology as a process of work with a multitude of effects in organisational life.

The selected ethnographic site is a credit scoring centre (CSC from now on) that has received the pilot test licence to conduct consumer credit reporting. The CSC is an independent entity registered by one of the largest internet companies in China, but it runs as a department inside its financial technology division. The internet company has their own lending products as well, which the CSC also conducts risk management for. The internet company also possesses a significant amount of proprietary user data, including users’ social media data, communication data, payment transaction data, consumption data, gaming data, investment data, and data from various other applications on its platform. The volume of daily payment data on its platform alone reached one billion transactions in 2019.

### 3.1 Reflexivity

A side note: between 2016 and 2019, the western media has covered the Chinese social credit system like it is the overarching rating system portrayed in the Black Mirror Netflix series (episode 'Nosedive'). This fits evokes a 'big brother is watching' narrative that draws inspiration from the book *1984* by George Orwell (1949). They see that this government project is creating a system where it is compulsory for all personal data to be fed into a central database and rating mechanism with the goal of auditing citizens and tightening surveillance. However, the qualitative data and observations from the field show that the reality is more contested and less unitary than these accounts might suggest. The  construction of Chinese social credit is a complex experimental process that involves multiple counterparties across different levels of government, cities and institutions. Overall, it is a social engineering process, where different understandings and innovations have emerged across different counterparties and are shaped by different stakeholders.

By the time when I went into the field, discussions about what should be understood as 'creditworthiness' were still ongoing. The fragmentation of data sources was evident. There was not a single centralised database of various datasets. For example, large internet companies had collected a considerable amount of daily personal data; the PBoC's credit reporting centre had collected credit data; and the state council was compiling data from people who had been added to a blacklist of dishonest behaviour or who had a court history. Several cities, such as Hanzhou, Suzhou, Fuzhou and Zhuzhou, tried to implement social credit scores on a local and experimental scale in an attempt to build their datasets. Moreover, the PBoC had given a test licence to eight companies to create credit scoring models, which they had initiated, relying on a small team of their model developers to sharpen their credit models.

Based on the contrast between hyperbolic media reports and seemingly more nuanced accounts from the field, the motivation and the selection of topics of this thesis was to offer a more realistic social study of the Chinese social credit system, and to delineate how a large government project was being enacted by participants on various levels. As a social scientist, I was drawn to understanding the social configuration of such technology; how the calculation for a rather complex notion of ‘creditworthiness’ is specified into several variables for measurement. Meanwhile, given the days and nights spent with the team of model developers, I could relate to their struggles. As a social scientist, I felt responsible to understand the impacts of algorithmic calculation and the particular embedded calculative culture that could be observed. These thoughts provide the anchor for this thesis, which revolves around a sensitive government project.

### 3.2 Access to the field

Gaining access to participatory observation of credit score development was the most difficult part of this project. This was mostly due to the sensitive nature of the government project and the secrecy around the issue of credit rating by the individual companies. The controversies around algorithmic measures further contribute to sensitivity. Practitioners in the eight companies were sensitive about revealing information because, at that time, these eight companies were expecting the central bank to issue the final official licence for credit reporting, while the central bank was holding back on issuing such a license. It was at that particular point that they were reluctant to reveal information that would subject them to greater controversy.

During the early phase of this research, I learned about the phenomena and tried to understand the major contributors to this government project: i.e. ‘who is doing what?’ I started contacting people involved in the eight credit rating companies through LinkedIn and tried to establish connections with them since December 2017. Many of them remained sceptical about the idea of talking to me. I kept asking them for help and guaranteeing them anonymity. I approached product managers to discuss the localisation of credit scoring in China. I realised that these practitioners were interested in learning more about credit rating agencies abroad, because they were facing challenges in defining creditworthiness and choosing which data should be included in their own models. Thus, I seized the opportunity to have a conversation with them and conducted interviews.

By March 2018, I managed to interview six product managers and one model developer from the eight companies selected by the PBoC. However, these interviewees were not senior enough in their organisations to grant me access to the field. By that time, it seemed impossible for me to be able to obtain access to the field. Initially, I tried applying for jobs in one of the eight companies, but the positions were not best-suited for this study. In April, I met an academic from Beijing University in London who has written substantially about credit scoring in China. He had worked at the PBoC and is well-connected in this area. I mentioned that I was doing a PhD on credit scoring in China, and asked him whether I would be able to study at one of the firms. He mentioned that one of his friends works as the director of one the centres and he might be able to help me.

Before the academic had formally introduced us, I had already connected with the centre director, so when the introduction was made, the connection between the director and myself was reinforced. I followed up to contact the director and scheduled a call. He proposed that I could study how his team works while I simultaneously worked for them writing up a research project that was given to the centre by the national internet finance association of China (NIFA) on a standard for personal credit data collection. I then contacted the human resource staff for an interview, and discussed the date and access to work. On 8 May, 2018 I arrived in the field.

### 3.3 Building relationships in the field

**Upon arrival.** In the initial phase of the participation observation, I was working with the centre director and the modelling supervisors on the research project. Because I was a newcomer, a modelling supervisor was assigned as my mentor. The modelling supervisor was aware of my intention to study their work and asked me what I was hoping to learn, in order to help my research. I told him that I would like to understand how the qualitative understanding of default and creditworthiness features in the configuration of credit modelling. He didn't really understand my question, and told me that what they do in the team is purely quantitative. Due to the disciplinary boundary, he didn't really understand my topic of study either. This lack of understanding, paradoxically, might have turned out to be helpful; as time went on, they seemed to forget that I was studying and observing them.

**Reaching out and building relationships starting from first acquaintances.** One of the colleagues asked me at dinner whether I was a 'spy' brought in by the director or by other foreign companies. Although initially I was seen as a 'spy', trust was built through the relationships that I developed. Whilst working on the research project, I reached out to other colleagues who had also worked briefly on the project. I started by building relationships with them. Later, they helped me to connect with other colleagues. These two colleagues helped me understand what each of the colleagues was doing, and I could ask them to clarify anything that confused me.

**Becoming one of them.** Over time, by seeing these colleagues from 9am to 9pm and having lunch and dinner with them every day, I gradually became a part of the team, became 'physically and morally a part of the community' (Evan-Pritchard, 1964. p.77-78), even though I did not participate in their core business, which was modelling. We were even together on Friday night hangouts. I constantly asked them what they were doing, and how their day was. I followed each step of their modelling activities closely. I felt very grateful that I was slowly being accepted as a member of the group despite our different backgrounds. We reached a stage where we felt comfortable freely sharing our thoughts when we faced difficulties or struggles. We began to spend more time together at team events and in computer gaming sessions, which deepened the relationships.

**Leaving the field.** The consideration of how to maintain the relationships and keep in contact after I left the field brought me anxiety. Prior to my departure, I prepared a small card for each of my colleagues. I sat down with the modelling supervisor for two hours on my last day where he spoke more about his concerns with the models and his worries as a modelling supervisor. Surprisingly, after I left the field, my colleagues were more open with me in terms of what they thought about the modelling, and they shared their thoughts on the leadership and overall trajectory of the team. I was the person who understood their organisational life, whereas I am no longer part of the team. This gave me the opportunity to ask more questions and review the experience while in the field and also after I had left.

## 4. Overview of the three papers

The above questions in the three major areas concerning data analytics and algorithmic measures, influence and guide the way in which this thesis unfolds. The three main empirical chapters of the thesis provide answers to these questions through examining the three different dimensions of this technological creation: a) how the data analytics (data science) work is organised; b) organisational-level strategic responses to the state project; c) and, ultimately, the societal consequences of this modelling practice on the quantification of creditworthiness.

These three empirical chapters, as a whole, recount the different stages in the phenomenon: the first stage is the state of art in organising data analytical work of building credit scorecard models; the second stage is to trace back to the beginning stage of organisational strategising of how to implement the technology and meet the state programme, examining the main local actors involved in this process; the third stage is to consider the after-effects or real-life consequences credit modelling.

**The first empirical chapter,** entitled 'Organizational Fallibility in Affordance Implementation: Organizing Data Science Work at Scale', is concerned with how data science work is organised on an industrial scale. Data science work as a new job category has emerged in recent years, yet how data science work is organised has not been fully examined. In particular, data scientists need to deal with emerging forms of intangible material (i.e. data) and technical equipment (i.e. computer hardware and software), which require a unique combination of knowledge (i.e. statistics, mathematics, computer programming and knowledge of the business subject matter at hand). This empirical chapter reveals challenges that arise in the observed company's way of organising, which conjectures that similar organisational processes are likely evident in other technology companies that carry out data science work on an industrial scale.

This first paper is based on the ethnographic account of fieldnotes and interviews. The findings offer a closer look at how the field of big data modelling work is arranged and what organisational effects it produces. The chapter describes data science work as a continuous, repetitive and pre-prescribed process. Data scientists believe that the results are better when they have more data available, which leads to an endless acquisition for more consumer data. However, the division of labour between different organisational departments creates data barriers and presents struggles for gaining data access. The findings therefore emphasise the importance of taking into consideration resource boundaries (such as data barrier). This paper identifies a weakness in neglected social and organisational elements in technology implementation that brings such resource boundaries into existence.

Conceptually, the first chapter re-evaluates the concept of ‘affordance’ - what the technology can afford to do to suit organisational purpose. This chapter coins a concept ‘Organisational Fallibility’ to highlight that organisations may fail in realising the promise of technology, especially when individuals contribute with their own goals into the technology. Second, the chapter contributes by studying outcomes of implementing perceived affordance. Third, it calls for more attention to be given to the importance of understanding the social and organisational influences that shape affordances that can bring conflicts.

**The second empirical chapter**, entitled ‘The Mountains are High and the Emperor is Far Away: Local Rendering of State Calculative Technology’, draws attention to the organisational level of innovation in the state project of building a social credit system. In seeing how credit scoring serves as a tool and a calculative technology to govern consumers via monitoring and quantifying consumers into numerical subjects, this paper is concerned with the political rationale for using this calculative technology and the gap between the political aspiration and local organisational technology delivery.

Based on interviews comprising eight organisational accounts of building credit scoring technology for the state project and government documents for understanding the state aspiration, this empirical paper explores the intricate linkages between calculative technologies and demonstrates how the state programme is manufactured through meso-level actors. This unpacks the localisation process of the state programme, in which organisations conduct sense-making, strategising and strategic adaptation. The findings emphasise that organisations render local resources and organisational dispositions while innovating technologically, turning calculative practice into an ever-expanding process of product optimisation, which as a result, alters the original state programme.

This paper uses governmentality lens to recount the organisational effort of adhering to a state-led programme, while adapting the technology for a purposeful commercial end. It contributes to the accounting literature of calculative practices and by proffering an understanding of meso-level effects in shaping calculative technologies. It thus brings ‘governmentality’ into interpreting technological innovation in the Chinese context. This paper informs regulators who are building a state project to pay attention to the unintended consequences brought about by transmitting and delivering the political rationales.

**The third empirical chapter**, ‘Credit Modelling in an Algorithmic Cage: How a Calculative Culture Affects Access to Credit’, uncovers the impact on consumers and society of the recent transition from traditional economic modelling to AI-based big-data algorithmic modelling. It offers an examination of model developers’ beliefs and ideation behind their practice of using statistical and machine-learning algorithmic results to build credit models. This paper focuses on modelling culture and provides a close inspection of the processes whereby how algorithmic injustice materialises in shaping access to credit.

Based on the extensive ethnographic data of credit modelling, the findings show that model developers believe machine learning algorithms have higher explanatory power to understand human behaviour. They rely on statistical and machine learning algorithms to select variables of high statistical significance. The pursuit of high results on statistical measures of model performance places the development of algorithmic credit scoring into an ‘algorithmic cage’ of its own making. As a result, the problem of data quantity and quality becomes more critical in determining the judging variables while modelling injustice is not eliminated. Moreover, due to the model efficacy, consumers whom the model cannot evaluate due to insufficient data are filtered out from access to credit. Furthermore, model developers run real-life experiments to gain consumer data to further target specific consumers, which proactively shapes needs for credit.

This paper provides an in-depth analysis of the roles played by big data and algorithmic machines in the production of a quantitative measure. It contributes to an understanding of a reductive calculative culture that turns the evaluation of creditworthiness into a simple judgment of statistical significance. Moreover, it attends to the performative effect of the credit models, through showing how injusticed data emerges and how modelling practices shape future access to credit. This research might also be of interest to those concerned with the quality control of algorithms by highlighting the links between algorithmic injustice into the discussion of financial inclusion.

## 5. Contributions and organisation of the thesis

The findings of this thesis contribute to understanding the modelling work in the production of algorithms, its technological design in organisational innovation for state governance, and its culture surrounding algorithmic practice and consequently its impact on consumers' financial life. Overall, this thesis empirically documents the processes underlying secretive algorithmic technology production and interrogates some fundamental issues behind it, such as the current problems of organising data science work, which leads to the fight of data and overfitting models; A political rationale and aspiration of a state programme can be hijacked by local organisational strategising; Moreover, the reductive calculative culture of current practice of credit modelling, which does not ease algorithmic injustice but, on the contrary, further perpetuates it.

In terms of conceptualisation and theorisation, this thesis situates itself in the domain of the social studies of technology and accounting literature of calculative practice, which enables this thesis to ask and answer interdisciplinary questions and makes contributions to furthering the connection between these two domains. Specifically, the first paper establishes the concept of ‘organisational fallibility’ to aid the understanding that organisations may fail in the process of implementing technological affordance; the second paper coins the concept of ‘local rendering’ to enhance understanding of the importance of micro- and meso-level adaptations of macro-level programmes; the third paper brings attention to the ‘algorithmic cage’ that puts credit modelling onto a narrow-sighted path, which leads to the incubation of algorithmic injustice. On a whole, this thesis contributes to the literature on technological affordance, governmentality literature on calculative technology, and literature on calculative cultures by developing a richer understanding of algorithmic credit scoring in China.

The thesis is structured as follows. After this introduction, the three empirical chapters unfold. Each of the empirical chapters consists of a full and stand-alone research paper. As introduced, chapter two explores problems arising in current organisation of data science work and the underlying reasons; Chapter three recounts the organisational process of technological innovation and technological delivery of the state programme. Chapter four pays close attention to the current modelling practice behind configuring credit technology, which informs about its impact on credit access in consumers’ financial life. Finally, reviewing what this thesis achieves, chapter five discusses the overall findings, underlying implication and proposes implications for future research. Some samples of field materials are also included at the end of this thesis (in Appendix II).

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# II. Organisational Fallibility in Affordance Implementation: Organising Data Science Work at Scale


## Abstract

This paper examines how and why the actualisation of perceived technological affordance can lead to negative consequences for organising data science work. Current literature on affordance for organising has still to consider many of the outcomes of the actualisation of technological affordance in the area of data science. This is important, as many organisations are building Artificial Intelligence/Machine Learning models and need to understand how such models engender organisational challenges. Based on ethnographic fieldwork in the credit score modelling team of a large internet company in China, this research recounts the development of data science algorithmic credit-scoring technology. Attention is paid to how the perception and actualisation of technological affordance in the organisation have an impact on shaping the emerging technology, which precludes data scientists from fully meeting their objectives. First, it notes that data science work is a continuous, repetitive, and pre-prescribed process of developing and updating models, relying on complex machine-learning generated results. Yet the perceived affordance of machine-learning algorithms alters the form and content of data science work, leading data scientists to fight for more unknown data as a resource with which to improve models continually. Second, it witnesses a division of labour between different organisational departments, which reinforces organisational boundaries and effectively creates data barriers. Third, the way in which the data science team's performance is measured has an impact on the efficacy of the models. These ethnographic realities of data science work allow us to offer fresh insights into organisational fallibility in affordance implementation.



**Keywords:** Digital Affordance, Organizing, Credit Scoring, Artificial Intelligence, Machine Learning, Data Science Work

## 1. Introduction

This paper examines what happens when organisations actualize their perceived technological affordance in the process of organizing. It builds on earlier work (Leonardi, 2011; Zammuto et al., 2007) that recognizes technology affordance, allowing new opportunities for organizing. Affordance is defined as 'to what an individual or organisation with a particular purpose can do with a technology' (Majchrzak and Markus, 2013, p. 832). It adds to this literature and studies the outcomes of actualising perceived affordance when an organisation fails to deliver on the technology they develop, exhibiting a dark side of information technology (Tarafdar et al., 2013). It coins a concept for this phenomenon—'organisational fallibility'—to highlight that organisations may fail in affordance actualisation and identify a blind spot of neglected social and organisational elements in technology affordance.

This research provides an illustrative example of how emerging technologies, such as Big Data analytics and machine learning algorithms, are perceived and integrated into data science work to achieve organisational capabilities. It examines the use of technology in the organisational process by which Big Data credit scoring models are produced at a large Internet company in China. It conjectures that similar organisational processes are likely evident in other technology companies that carry out data science work on an industrial scale. Affordance is employed as a key concept because it offers a productive lens to observe the imbrication of social and material agencies in processes of organising. As Leonardi (2011) discusses: 'as people attempt to reconcile their own goals with the materiality of a technology, they actively construct perceptual affordances and constraints' (p.154). Likewise, this study delineates an emergent and continuous process of organising where perceptions of affordance held by organisational members and data scientists are presumed to play a role in processes of organising and technology implementation (Orlikowski, 2000).

The research is set in the context of Big Data credit scoring in China, where the credit scores produced were expected to rate the entire population as part of a state-sponsored programme of building a ‘social credit system’. In that system, credit scores are used as quantitative indicators, not just of creditworthiness, but as raw material for a whole gamut of other services that one might obtain by demonstrating social worthiness more broadly.

Recent literature has explored the interrelated and co-constitutive relationship between the design and practice of technology in organisational settings, as well as the arrangement and coordination of work (Jones, 2014, 2013; Barrett et al., 2012; Nicolini et al., 2012; Orlikowski, 2007, 2000; Fayard and Weeks, 2007; Pentland and Feldman, 2007). Such work aims to better understand the current changes in organizing and work (Leonardi and Barley, 2008; Zammuto et al., 2007) that are engendered by different technological affordances , they call for more research to address the significant neglect of technology in the management literature.

Big Data has enabled social analysis (Lazer et al., 2009) and statistical analysis of social data on an industrial scale (Barley, 1988), analysis containing both old and new elements of knowledge (Boyd and Crawford, 2012) and forms of intervention (Marres, 2017; MacKenzie et al., 2015; Latour et al., 2012). Quantification renders people visible and permits remote monitoring and governing (Scott, 1998; Miller and Rose, 1990; Espeland and Stevens, 2008). Through ‘data extraction and analysis’, ‘new contractual forms’, ‘personalisation and customisation’, and ‘continuous experiments’ (Varian, 2014, as cited in Zuboff, 2015, p. 78), organisations apply ‘data science’ (O’Neill and Schutt, 2014) to understand consumers through the creation of a digital depiction of consumers’ abstract forms (Fourcade and Healy, 2013, 2016) and behavioural classifications (Mayer-Schonberger and Cukier, 2013). This form of practice facilitates and enhances an organisation’s ability to understand and penetrate consumers’ personal lives, creating a quantitative form of organisational knowledge (Faraj et al., 2018) and an advanced capability to target, interact with, and control individuals (Zuboff, 2019).

These practices of rendering (Zuboff, 2019) are underpinned by existing literature that notes the development of digital technology as bringing about a new type of work, replacing some other roles while modifying the remaining portions of the organisation (Barley and Kunda, 2001; Adler, 1992; Barley, 1988). Data science is one area in particular. Likewise, data science has emerged in great demand among organisations. For instance, a survey (Lorica and Nathan, 2018) conducted by the O'Reilly Group among 9,700 companies in North America, Europe, and Asia showed that 15% of them had implemented a Big Data model in production for more than five years. Lorica and Nathan (2018) characterise these companies as sophisticated data science users. Some 36% of the surveyed companies are early adopters, with models in place for two years. The remaining 49% say that they are seeking to adopt models in production. McKinsey and Company (2016), in a report entitled *The Age of Analytics: Competing in a Data-driven World,* describe organisations attending to the need for data scientists, assuming their presence alone will enable an analytics transformation. The U.S. Bureau of Labor Statistics shows that 11.5 million jobs in data science or an analytics area will be created by the year 2026. However, as a potentially new genre of work, Big Data modelling work has not yet been sufficiently delineated or studied empirically (Holtzhausen, 2016; Constantiou and Kallinikos, 2014). We offer such a study here to build conceptual insights into the realities of technology affordance in organisational settings.

Scholars (Leonardi, 2013, 2011; Faraj and Azad, 2012; Yoo et al., 2012; Zammuto et al., 2007; Hutchby, 2001; Gaver, 1996) have found the concept of affordance (Gibson, 1986) useful for studying the design, use, and practice of technology, as affordances for organising can bring opportunities for change in organising, such as alteration of organisational functions and work. This literature has laid the foundations for envisaging the role of technology in organisations. However, this branch of research does not consider all the outcomes of actualisation technology affordance for organising work. Many questions such as ‘what technological entailments imply for organisations, their norms and forms of structuring, their capabilities to act and interact, their performance of current and future strategies, and their possibilities for innovation and learning?’ (Orlikowski and Scott, 2008, p. 436) have not yet been answered. Extant research tends to presume that the outcome and effect of actualisation will change organisational practice. As Leonardi (2011, p. 147) projects, ‘the perception of constraints lead people to change their technology, the perception of affordances lead people to change their routine’.

This paper proposes that the implementation of affordances may bring about negative outcomes as well as positive ones. In doing so, this research makes three key contributions. First, it problematises the actualisation of digital affordance and shows that the organising process itself may lead to negative consequences. Second, it draws attention to the concept of organisational fallibility to understand how affordance actualisation can lead to blind spots, such as enforcing resource boundaries and self-fulfilling prophecies—especially in the form of individuals inputting their own goals into the emerging technology. Third, it calls for more attention to be given to the importance of understanding the social influences that shape affordances. It also empirically aims to open the black box of how Big Data modelling work is coordinated and what organisational effects it produces. These are poorly understood areas and little-studied hitherto.

This paper is organised as follows: after the introduction, I present the theoretical framework and literature review of the current understanding of affordance for organising in section two. Then, in section three, I examine the study’s underlying context and introduce a larger societal background. In section four, I present the methodology and data collection and data analysis processes in detail. Findings and discussion are outlined in the fifth section, wherein I detail the current process of Big Data modelling work and what this means for the actualisation of technology affordance. Finally, section six concludes with the study's main contributions and suggestions for future research in the areas of technology affordance.

## 2. Theoretical background and literature review

### 2.1 Actualisation of affordance varies in context

Hutchby (2001), a sociologist, points out that affordances can lead to different actions in different contexts. He studies technology as texts and sees affordances that are inherently external to humans. Humans interpret materiality as desirable (Schatzki, 2010; Pels et al., 2002) and accordingly carry out actions around, or via, an artefact out of will. This suggests that artefacts cannot impose themselves on humans. Human perception and action are both important. Different users may perceive that the same technology affords different actions; thus, possibilities of action and interaction of responding to various affordances can vary. Hutchby points out that the same technology may afford different actions for the same user in different contexts.

Using the example of Wikipedia, Mesgari and Faraj (2012) argue that affordance is not confined to technical features but also extends to social and user dimensions, adding a socio-material aspect when looking at affordance. Mesgari and Faraj (2012) propose social, user, and technical as the three dimensions of technology affordance, while their influence on shaping affordances might differ based on the technology and its context. Following this, Fayard and Weeks (2014) reaffirm the importance of perception in affordance and recommend encompassing affordance within Bourdieu's (1984) idea of *habitus* to complement the understanding of how practice is patterned by social and symbolic structures to unravel intricate social and material entanglements. Despite this, the question of how these social influences shape affordances has not yet been resolved.

Provided with these, we are informed that the actualisation of affordance may vary from context to context. However, the question of how these social influences shape affordances has not been fully explored. Given the findings in this research that organisation actualising affordance in an organisational context may not lead to a positive technological delivery. Further literature should be developed to understand the social shaping of affordance.

### 2.2 Socio-materiality of technology and the organisation of work

The social shaping of technology, a social constructivist perspective (Pollock and Williams, 2008; Bijker et al., 1989; MacKenzie and Wajcman, 1985) subscribes to a voluntarist view and has long offered an alternative lens to technological determinism (Dierkes and Hoffmann, 1992; Leavitt and Whisler, 1958), which renders technology an outcome of its inner-logic and as being materialistically determined. Yet, Leonardi and Barley (2008) argue that materialism and voluntarism can be reconciled, disrupting the dichotomy between human agency and determinism. They criticise approaches to technological determinism that often neglect the roles that people play in bringing about the effects of technologies on organising. In turn, social constructivists seldom address the materiality of technology in terms of the constraints and affordances it presents. A more balanced view of observing the interplay of the social and the material, and the social and the technical is required. Leonardi and Barley (2008, p. 63) surpass the study of technology as a static subject, perceiving it instead as ‘operationalising technology as a constellation of processes, and work practices’. I seek to build on this work here.

However, in an analysis of the field’s leading management journals, Orlikowski and Scott (2008) revealed that over 95% of articles viewed technology as ‘discrete entities’ and as an independent or moderating variable contributing to communication, coordination, and control (Huber, 1990); they do not consider the role of technology in organisational life. This framework inhibits researchers from seeing the human and organisational elements in shaping technology or from attending to the material properties and features of the technology that define a frame for work and organisational life (Orlikowski, 1992).

Orlikowski (2000) argues that work is often organised based on the material properties of a technological artefact, such as software, and that the software's features constrain the available workflows. Pentland et al. (2012) further explain organisational routine as a socio-material ensemble, involving a combination of actors such as the intertwined social and technology. Meanwhile, socio-material ensembles are increasingly integral to organisational capabilities, determining what an organisation can achieve.

In this research, we see algorithmic credit scoring technology as a development of routines, where workflows are built upon the social (organisational arrangement, organisational structure, organisational coordination, expertise, and work of data scientists), material hardware (computers, servers, storage, networking, and CPU), and software systems (OS, analytical software, databases, etc.). Given such a lens, this research evaluates the process of how data science work is performed and how organisational life is integrated with the actualisation of technological affordance. As such, this study can examine the impact of a perceived affordance on the work process and provide a detailed analysis of the organisational environment for the actualisation of technological affordance, considering the roles of both social factors and materiality in shaping the outcome of technology.

### 2.3 Technological affordance and the organisation of work

The concept of affordances originates in ecological psychology by Gibson (1977), who coined this concept to describe how animals and humans perceive environmental conditions in relation to the needs of their actions. Gibson explains that it is the perception of material affordance that prompts behaviour and actions in an environment.

When affordance was introduced to understand technology and design, Norman (1988, p. 9) defined affordance as ‘the perceived and actual properties to things, primarily those fundamental properties that determine just how things could possibly be used’. His focus was drawn to the explanation of affordance in regard to constraint. He adds in a later work (1999) that affordance involves perception, as individual behaviour is caused by the environment’s perceived affordance, not the material affordance of the technology itself.

The propelling use of the concept of affordance in Information Systems research embraces Norman’s (1988) idea of affordance. Zammuto et al. (2007, p. 752), for example, explain that ‘an affordance perspective recognises how the materiality of an object favours, shapes, or invites, and at the same constraints, a set of specific use’. Their research later discusses affordances in the practice of implementing an enterprise resource planning system that may change forms of organising. Leonardi (2011) further enriches the concept of affordance. His research is of specific interest to this research in three respects: First, he explains the imbrication of human and material agents in affordance and specifies how human agents can imbue their goals into technology or change the environment to achieve their goals. Therefore, changes are induced from an understanding of the array of imbrications between human and material agencies. Second, he strives to understand affordances in relation to constraints by viewing them as opposite sides of technology’s perceived capabilities, considering people’s goals and specific contexts (Cohendet and Simon, 2016). Human agents can modify the effects of constraining technologies (Boudreau and Robey, 2005). Third, Leonardi (2011) defines affordances as socially constructed, emphasising that material and human agencies are actively reconfigured in work practices.

When Leonardi (2013) later touches upon how affordances and constraints are constructed, he draws attention to the importance of the shared affordances. He demonstrates that when people use the same features of new information technology, such as computer-based simulation technology in automotive engineering, people share a perceived affordance—that the shared affordance shown in a group-level network makes a difference in the adoption of behaviours in organisations. He suggests the disposition of sharing technology as a resource and shared affordance can enable the group to change the content and structure of the group's advice network. The shared affordance helps us to understand that the only cases that makes data sharing easier is through productisation with other business partners in our research. If it is only through productisation that a shared affordance of the technology is created, data sharing coordination becomes easier through the same process.

This stream of literature has offered a lens for this research to regard the use, design, and implementation of technology while underpinning its impact on routine and arrangement. However, this study aims to evaluate more organisational elements and individual elements that come with affordance actualisation and evaluate how organisational fallibility can take place in affordance actualisation, as current literature on affordance for organising has still to consider many of the outcomes of the actualisation of technological affordance.

## 3. State programme: Political rationality and credit scoring in China

With the Chinese government aiming to promote a consumer society (Ding, 2015) and enacting an economic transition from an export-driven economic model to one led by domestic consumption, attention has shifted to the creation and use of credit by Chinese consumers (Xinhua, 2016). According to Moody's, shadow banking—or off-balance-sheet— lending in China increased to $9.4 trillion in 2016, accounting for 87% of total GDP. This can be traced to the exuberance of internet finance, outside formal banking. Rapid credit growth raises concerns, as bad debt loads can arise due to a shortage of effective methods of credit risk management (Elliott, 2017). Debates have arisen about whether the debt level exceeds a manageable level.

Internet finance, including any kind of internet financial applications, provides non-bank enterprises or individuals with a platform to expedite loans to small enterprises or other individuals. Given that state-owned banks often prefer to lend to state-controlled entities, the development of internet finance in China has created a new means of investment opportunity and a new means of financing since 2013. Moreover, different credit instalment products have recently appeared in China, generating, as a result of information asymmetry, a higher risk exposure for lenders. In internet finance, applications are made online, and the loan is automatically approved based on verifying and auditing the applicant through available data. This has led to an explosion of lending, loosening the standard of borrowing due to lax regulations and creating an urgent need for effective assessment technology and automated information sharing.

A series of incidents, such as internet finance borrowers running away from their liabilities in 2015, has drawn the government's attention (PBoC, 2015). The central bank officially set up a committee to study financial technology in 2017, seeking to 'strengthen the actual implementation of regulatory technology (RegTech), indicating that the application of Big Data, cloud computing, artificial intelligence (AI) and other technologies will be used under enhanced scrutiny in future years' (PBoC, 2017). To this end, the Central Bank of China (PBoC) posed a challenge for the industry to develop new risk management technologies and take advantage of the accumulation of data offered by digitalisation.

A document entitled ‘Planning Outline for the Construction of a Social Credit System (2014-2020)’ published by the Chinese State Council in 2014 laid down concrete requirements for relevant parties to build a social credit system as ‘an important method to perfect the socialist market economy system, accelerating and innovating social governance’. Moreover, the 13th Five-year National Development Plan (The Chinese State Council, 2016) includes accelerating ‘the construction of a social credit system to cover the whole society and to praise integrity and punish misconduct’ as one of its main tasks.

In 2016, the government appointed eight Chinese companies with different datasets and strengths to use online data and algorithmic scoring methods to calculate personal credit scores to accelerate the collection of consumer information and create an effective algorithmic model for calculating creditworthiness. These companies built technology to scrutinise citizens’ multidimensional social behaviours, examining their financial, education, and web browsing information, as well as other personal social data, to evaluate lending risk in China. Unlike traditional credit scoring, its application extends from measuring one’s ability to repay loans to the measurement of overall general reliability—both creditworthiness and social worthiness.

The eight credit scoring companies (see Appendix I) accessed their connected proprietary Big Data and other data sources to detect fraud and calculate lending risk for online lending business and consumption instalment credit companies. As pilot companies, they had access to the People’s Bank of China (PBoC) credit history record system, which, at the time, only had a credit history of 380 million people. However, their task remains to identify other data by which to assess people without a PBoC credit history. Due to large demand, by January 2018, the company we studied—one of the eight companies—reached eight million daily inquiries of their credit score system although it had not launched its product to individual consumers yet.

## 4. Research setting and methods

### 4.1 Research setting

One of the authors conducted an on-site field study of a Credit Scoring Centre (CSC) in a large internet company in China. The company possesses a significant amount of proprietary user data, including users' social media data, communication data, payment transaction data, consumption data, gaming data, investment data, and data from various other applications on its platform. The CSC is affiliated with the Financial Innovation Branch (FIB), which manages its payment platform. Given that China has become a largely cashless society in which digital payments are commonplace, as of 2019, the payment platform effected one billion daily payment transactions. This organisation's platform stores a vast amount of information related to payment transactions, consumption, and investment, all of which occur via its payment platform.

The CSC has tailored its products for ID verification, blacklist checking, whitelist checking, and provision of a credit score. In particular, the first version of their basic scorecard model in 2017 was trained to score the whole population of China for the state-approved pilot project described in the previous section of this paper. It reached three million daily inquiries from banks and internet lenders before its launch for consumer inquiry; however, the product was called off one day after its launch to score consumers. After this, its test license was revoked, and the project was restructured by the Peoples Bank of China. The models' results are now used by the company's partners, which include mostly internet lenders and car loan providers. During the observation period, the CSC was still trying to update the basic scorecard model to achieve a higher model predictability.

### 4.2 Research methods

This research has collected first-hand qualitative data. Primary data include ethnographic observations, semi-structured interviews, and archival documents. These capture the phenomenon while exploring the construction and practice of the technology in the work process. In addition to interviews, observations, and experiences, I draw on several additional data sources, including documents outlining workflow, work standard, model building, variable selection, regulatory policies, and statistics.

The researcher initially conducted 25 interviews with product managers and data scientists involved in the credit-scoring process from the eight organisations selected by the PBoC to prepare to develop the credit-scoring business. Through these semi-structured pilot interviews, ranging from 50 to 120 mins, we collected real accounts of how the credit-scoring business in China came into being and the logic behind the technology's design and practice. Consequent interview data helped us to construct a map of the credit-scoring business in China, enabling us to unravel the phenomenon and gather detailed information about the components and actors involved and to make an informed choice for the ethnographic site for observation.

For the study of the organisation process and the human practice of a technological feature, what is happening in the field (Czarniawska, 2004, p. 7) and in practice (Beadle and Moore, 2006) is substantial for understanding the affordance actualisation and its effect in the process. As Garfinkel (1967) once revealed, the nature of ethnographic work as a 'study of members and knowledge of his ordinary affairs, of his own organised enterprises where that knowledge is treated by us as part of the same setting that also makes it orderable' (p. 11).

In this research, ethnographic data were gathered by the first author from 695 hours of participant observation over a three-month period from May to

August in 2018. The observer kept a daily research diary, incorporating detailed fieldnotes for every day at work and off work, generating 469 pages (both hand-writen and typed in single-spaced 11-point font with standard margins) of fieldnotes and 15 two-hour meeting transcripts. The observer was immersed in the ethnographic site for a long period every working day due to the company's long working hours and involvement in a ritual that included the whole team having lunch and dinner together.

The participant observer's role in the team by the time is to carry out and write up for a research project about the standard for individual credit information collection for the National Internet Finance Association of China (NIFA). This offers a close chance to work with the data scientists. The most important settings for data gathering were daily observations of modelling work and the company's weekly meetings. The data collected in this research were derived from ordinary conversations between the employees in the group, daily work routines, and their daily interactions with co-workers and clients. The observer took extensive notes on the activities of staff members, ranging from directors to data scientists. The weekly meetings functioned as another primary source of data because they involved group members and the director going through each process of every model built, as well as the current status of the specific projects on which they were working. Intensive details and quotes were used to document the meetings. Most of the meetings were recorded.

Ethnographic fieldwork was augmented by semi-structured interviews carried out after the ethnographic observation. In total, semi-structured interviews added 24 hours of recorded interview material, supplemented with notes from observations and experiences in the field. These interviews were conducted with the director, group leader, and some of the data scientists. Notably, these interviews provided deeper insights for explaining the observational data and for discovering the underlying reasons for certain credit-scoring practices. These interviews contributed substantially to advancing the observer's knowledge of the data scientists' perception of technology in use and their practice in the organisation.

The data were inductively analysed in three phases. During the first phase, researchers interrogate the data for emergent contents and interactional patterns and recursively go back and forth between transcripts, original recordings, interviews, and fieldnotes (Yanow and Schwartz-Shea, 2006). Thematic summaries were outlined to speak out different components in data scientists' work. By doing this, researchers witness the work and routines are built upon various material artefacts. Our attention to organisational fallibility emerged in the form of a puzzle generated by a discrepancy between what I observed and the results of previous studies in technology affordance (Leonardi, 2011, 2013; Zammuto et al., 2007). The discrepancy lies in that I can see the role of affordance in shaping work routines and content. Still, the literature cannot help us to understand that the fallibility in the development of technology creates unintended consequences in organising work. In the third phase of analysis, I categorised three critical themes that can lead to organisational fallibility. This led us to identify specific dimensions for articulating the blind spots of affordance of organising.

## 5. Walking into the task environment of big-data analytic work

> [On the first day upon my arrival], the model supervisor told me: 'here, everything we do is purely quantitative. We are a pure quantitative team. So we use data to build models. You know in the model there is X and Y, so we build models to explain Y, like the relationship between the X and Y in the model...Later you will see'.
>
> – Fieldnote excerpt

The Credit Scoring Center (CSC) is situated in one of the buildings that belong to the internet company and operates as part of the company's Financial Innovation Branch (FIB), which cooperates with the company's set of payment platforms. The payment platform is connected to the company's social communication application. The CSC cohabits with other departments, sharing the same floor with some other groups in the FIB. There are four teams in the CSC: product manager team, IT infrastructure team, modelling team, and a commercial team. Product managers communicate with commercial partners or credit providers regarding new products. The IT team is responsible for building and maintaining IT infrastructure, and the commercial team contracts and negotiates with clients. They all belong to the FIB and are run as independent groups. The modelling team is responsible for the credit scoring technology, i.e., the basic scorecard model to score the whole population and other credit models for internal and external use. The models they build represent the basic technological capabilities of the CSC.

The modelling team comprises 12 people and includes the centre director, one modelling supervisor, and ten data scientists (model engineers). Specifically, they separate the data scientists into two groups: one is the basic modelling group, and the other is the application strategy group. The basic modelling group is responsible for building the basic scorecard models for credit scoring to differentiate good borrowers from bad borrowers. They develop models to quantify the relationship between different variables and the outcome of a possible credit default. The strategy group builds models to support certain credit development projects for the tech giant and its partners. Data scientists train models on large datasets to predict future credit events as accurately as possible.

Each data scientist in the credit modelling team is responsible for using a certain set of data to build models and to test them for deployment. There is little communication between data scientists during work. Each of them is assigned to use a statistical calculation method to build models and carry out experiments with the goal of enhancing the model’s predictability. Data scientists perform calculations on SAS, a statistical software suite, and perform codes on SAS to run the calculation and later view the outcome in the SAS window. The calculation is commanded through human and non-human agents (software and hardware). With people in the foreground and the exact calculation in the background of the software, the completion of the whole calculation involves the data scientist's knowledge to understand the calculation result and their judgment and computational skills to execute the next step.

The output of a model developer's work is a credit scorecard model. That is a predictive statistical model used to assess the credit risk level of a credit applicant. The credit scorecard model does this by providing a probability of failure. In its simplest form, a scorecard consists of a group of attributes or characteristics, statistically determined to be predictive in separating good and bad accounts (Siddiqi, 2017, p. 9). Therefore, to build a credit scorecard model, the objective is to find a significant correlation between different characteristics of borrowers and their default behaviours. The highly correlated attributes are then used in models to score credit applicants or creditors. With these attributes, the model is intended to calculate the possibility of default so as to generate credit scores for individuals. Correspondingly, each credit score is associated with a range of possible default rates.

Data scientists are constantly aiming to achieve higher model predictability. They aim to formulate models with strong predictive variables and then test how effectively the model will work on the testing samples. To achieve this goal, they experiment by building different sub-models to better explain and explore new datasets or by constantly adjusting their models. Data scientists are concerned about their models' predictability—they work by refeeding datasets and continually trying to achieve a higher predictability and a better performance of their models.

### 5.1 Standardised procedures and reliance on machine-learning

The work of Big Data modelling is organised to follow a standardised procedure. There are internal documents outlining each step of how to build a model, regarding each relevant constituent: i.e., the definition of a risk event, matching data, derivation of new variables, algorithm selection, selection of variables, and model output. These constituents in the process co-determine and shape the meaning and the result of the model. The procedure informs the data scientist about how to derive variables and how to refer to parameters calculated by the statistics software to select variables. The supervisor stresses the fact that the process is a well-established framework that has been used for two decades and is of scientific value. As such, the supervisor knows the process and checks the data scientist's work on key points of model development.

> The data scientists all follow a standardized procedure to build the model. They have documents identifying each small step. It has become a standardized procedure. The only person who normally walks around during work is the modeling supervisor. He goes to the data scientists when problems arise and checks on the key points of the model development. He is responsible for checking the quality of the model and gives instructions regarding how to proceed. Not much time is left to think about what the selected variables mean.
> – Fieldnote excerpt

The standardised procedure allows the modelling work to be manageable and controllable. As a comparison, in software engineering, quality assurance takes place to ensure that everything is executed correctly—verification is operated throughout the software development process. Similarly, supervising and monitoring data scientists' work at key points assures that the statistical calculations are appropriate. The supervisor believes that to operationalise Big Data modelling work, it is important that the data scientists follow the exact same procedure, so it is easier to control the model quality. If every data scientist follows the same process, the supervisor will know exactly how the result is produced. In the weekly meetings, the whole team exclusively reviews the summary of the model parameters. No deeper questions beyond those relating to the main features of the data sample are asked.

> I just need to check on the staff at a certain point because we have an established procedure for the modelling crew to follow. They just need to follow the procedure. By that, we can control the quality. Also, even if a new hire came to our bureau, in six months, he or she could totally build the model on his or her own. — The modelling supervisor

The standardised procedure of modelling work simplifies modelling into routinised work. It shifts the focus of the data scientist's work from understanding data and exploring the value and insight from data, to performing a routine cognitive process of calculations. In the case of standardising the procedure of model building, work is accomplished according to the established organisational process. With the procedure being clear, data scientists' work becomes easier. This permits work to be carried out without understanding the essence of the model creation or the meaning of data, eliminating the need for the high compulsory requirement for skill and knowledge in data science.

For instance, the observer followed a data scientist who was building a new credit model. She said that after matching all the data in the database, the next step is to derive new variables. She derived independent variables by breaking down the credit information into six-month, nine-month, and 12-month periods. The observer asked her why she was deriving these variables. She explained this by saying that this is a recognised industry practice, and it is a standardised procedure.

> They have massive data; therefore, while building models, they do data mining. They derive lots of variables from one piece of information. For example, they have someone's lending information from the previous 12 months. They can generate variables for putting

different time points: the highest amount of credit in six months, the average amount of credit in six months or three months, etc.
– Fieldnote excerpt

We can generate more than 1,000 variables from the central bank credit report from PBoC (one of their data sources). More than 1,000, therefore this combination can be plenty. Now we set up the process to use deep learning, we do not need to understand the raw text of the data or variables—for example, this raw text represents some kinds of lending products, but you don't need to know about this. Through machine learning, you will get the credit attributes. However, there is a very big problem [in] that these credit attributes do not have any meaning because we don't know what they represent; therefore, it's a black box.
– The director of the Credit Bureau

The standardised procedure facilitates data science work to be operated at scale, making the work manageable, controllable, and routinised. In most cases, it is less time-consuming and more efficient than data scientists regularly needing to innovate and re-invent workflows. Likewise, more models with new data sources can be produced in a shorter time frame. However, operationalising data science work at scale transforms craft activity (Sennett, 2008) into manageable routines—it lowers the understanding of each step and prevents the data scientists' work from being conducted more innovatively. When data scientists emulate their craftsmanship and continually seek to improve their craft, the belief and trust in the current process will shift the focus of improvement elsewhere, but not on the process itself. In such cases, data scientists believe that the breakthrough of improving their model's predictability lies in getting more data.

Data scientists need to build different sub-models targeting different groups of consumers, and they need to update models so that the result can be more accurate with the arrival of new datasets and updates to existing models. Data scientists follow a standardised procedure of building models, which allows the craftwork to be started, carried out, and managed more easily. However, the belief and trust in the current standardised procedure put the work at scale into a static impasse, preventing the work from being accomplished in a more innovative way.

### 5.2 Continuous and repetitive process of work

Big Data models are an updated combination of economic models that enable features of operational experiments. Big Data models represent what past data has to say about the correlation of a risky event. After such a model is completed, credit businesses rely on it to make inferences and predictions for future lending decisions. Big Data models are based on various real-life data. Moreover, it changes the static mode of modelling and places models into a framework of constant testing and experiments. After that, the model is used in the real-life setting, and user data can be fed back continually to allow re-training of the model. Such a combination of models and experimental features requires a constant refeeding of data and model results to tune the model.

The iterative nature of the process shows that Big Data modelling work is continuous and repetitive. To take advantage of the availability of Big Data proximating risky events of disparity, data scientists continually train the models with fresh data and adjust models based on the observed lending outcomes. If the data used to build the model is far different from what the model attempts to predict, this affects the model predictability's inference power. The team believes that to optimise model performance, it is critical to continually re-train the model with new data.

The scope of Big Data is immense, but Big Data modelling is still conditioned with one single modelling objective and constrained by sampling techniques. Each model should be understood and targeted to achieve one objective and account for specific events for a certain time interval. For models to be predictive, the CSC needs to build different sub-models targeting various risky events, such as ‘default in three months’ or ‘default in six months’. Models are produced through strictly controlled ways using sampling techniques that limit the scope, temporality, and size (Miller, 2010), which means the performativity of modelling is always circumscribed by how the model is being set up. This indicates models need to be perpetually recrafted, targeting a specific risky event. Data scientists need to clearly set up and flesh out the target-dependent variable to examine one objective.

> We use logistic regression, XGD models, and random forests (a machine learning algorithm) or other deep machine learning to construct our model. Perhaps you have different kinds of complicated algorithms—algorithms are just part of the modelling process. If you set the wrong target variable, then even if your model is great, it does not actually mean anything. Generally speaking, it’s just like garbage in, garbage out.
> – The director of the CSC

The right target dependent variable should depend on what constitutes a risky event in a quantitative form (Espeland and Stevens, 2008). So, what should be recognised as a risky event? Should it be the case that a borrower cannot repay within one week? Or the case that the borrower cannot repay within three months or one year? The threshold time to be used is arguable and can be contentious in operation, as different lenders have different risk appetites, or it can be influenced by the industry regulatory body or industry standard. Therefore, what can be seen as a risky event differs; however, with the advent of Big Data, data scientists concede a risky event to be defined by the data rather than using a fixed definition.

> For example, if one fails to repay debt, then we want to know how many days when one will be overdue. We then define overdue over 90

> days as a risky event. But then we want to look at consumers who default in 89 days; we try to see whether consumers had a larger number of overdue a month before. If it was 8%, this is very high. From here, I will know that if you default in 60-89 days, there is a higher tendency of getting worse. Then we will define consumers who default in 60-89 days as the risky event.
> – The director of the CSC

In adopting a data-driven approach to define the risky event, data scientists find it purposeful to target the accurate period in which most debts deteriorate. Later, they can set up a clear, dependent variable to capture the risk. However, this becomes completely dependent on the sample data distribution and where the risk exposure shows in that dataset. As such, the models need to be continually rebuilt for a different dataset coming from a different lending scenario. For example, if the bad debt sample (sample of the defaulted) is coming from a microlending product, its risk outbreak timeline could be shorter than that of a car loan product. If we use the model built from car loan data to predict default events in the microlending product, it will not be accurate to capture the risk outbreak; it will lose its inference power. This is why, sometimes, even though a model is good at predicting a certain event for a certain setting, it is not useful to predict another event. Therefore, data scientists are continuously and repetitively building different models or sub-models with different datasets (or with a newer version of the data) to keep their model updated so as to answer a specific question.

In addition, the sampling techniques set constraints. Data scientists must have an equivalent segment of stable and continuous development and testing samples to complete modelling work. Data scientists divide the sample data into two segments to prepare for model building—one segment for developing the model and one segment for testing purposes. One is from the observation period, and the other is from a performance period. This often sets a higher requirement for the continuity of the data and, at the same time, sets a constraint for the data that they can use. The absolute degree of autonomy of randomly including data of different forms is not valid. Data scientists necessitate sample data from the strict observation period. Having this enables them to establish continuous data to craft models that can continually explain the risky event in the same time interval.

> Our credit scoring model should be predictive, which means based on historical information, I can predict your future. Thereby, the observation period is the performance in the past, while the performance period is your future performance. Thereby, if I include information about future information [to build] a model to predict the future, it would, of course, lead to a higher predictivity. But then this high predictivity is not real.
> – The director of the CSC

The above is a speech that the director of the centre made to criticise the first version of the general scorecard model used to score the whole population. In that 2017 model, they made a mistake by including a specific static variable. One of the variables they used in their model was non-continuous data (only one month of the data is available in the ending observation interval). As a result, the model’s predictivity measure indicator was higher than it should have been, meaning the model parameter did not reflect the real predictivity level, as it used future data to predict future events. However, data scientists explain that this was an unavoidable circumstance, noting that one variable would not affect the general use of the model, and they did not have any other choice at that time but to include that static data item.

This highlights the difficulty in obtaining valid data that merits the scientific sampling requirement. Many independent predictive variables are still unstructured data. Very often, the useful sample size in the model building process is still rather small. Furthermore, the sample to be used in the modelling has a requirement of its strict temporality. Particularly when models are built with one dataset from a year when more creditors defaulted than usual, such as in a financial crisis, the model may carry the characteristics of defaults at that time. This may decrease its predictability on a usual credit period; therefore, its application of general prediction will be of little usefulness. Hence, in the process of sampling, data scientists will need to eliminate creditors who usually do not default, only doing so due to the financial crisis. In this case, the useful sampling size becomes even smaller.

Overall, Big Data scales up economic modelling with a critical dependence on the availability and characteristics of sample data. Moreover, later after placing models into an operational experiment, data scientists can adjust and update the model based on the result. A data-driven approach effectively targets a risky event with which to build a model while capturing the detailed characteristics of each lending scenario requires more dedicated work. Machine learning features and complex algorithms empower data scientists to identify more complex patterns and correlations, while the standardised procedure of data science work prevents the team from becoming more innovative and takes focus away from explaining the results. Big Data analytics with machine-learning features is a kind of paradox associated with the realisation of these futuristic technologies. Yet, behind the intelligent data analytics, it is more complex, repetitive, standardised work that keeps the models predictive.

Meanwhile, leaning on advanced statistical calculation and computational algorithms as an important component of work creates uncertainty. The use of deep learning algorithms means the calculation goes beyond data scientists' understanding and beyond their control. Before data scientists build the model, they have no prior assumption and control of what the model would turn out to be. In deep learning algorithms, as the calculation layers up, the results are difficult to comprehend (Von Krogh, 2018). In this sense, data scientists' work demonstrates a high level of uncertainty due to no prior understanding of what can possibly increase the model predictability and rely more on the sample data. In this case, the data scientists see the data as the strategic assets to enhance their model performance.

## 6. 'Big Data' as a scarce strategic resource worth fighting for

Big Data is an important factor of production for data modelling at scale. The ongoing modelling work and the pursuit of higher model predictability place emphasis and value on data access. Although Big Data has expanded the magnitude of data, structural heterogeneity in a dataset and the rate at which data are generated (Kwon et al., 2014; Gandomi and Haider, 2015), the discursive composition of the Big Data denotes that data is not as 'raw' or 'objective' and 'uncooked' as it might appear (Gitelman, 2013). Data is, in fact, an organisational construct with different actors working to connect and create a good flow of data sharing that is conditioned by political, commercial, and social relationships. Pointedly, the data composition of one analytic technology is an organisational construct dependent on the organisational environment. This research shows that it is highly constrained by organisational culture, organisational structure, and ways of organising work and resources.

Data as an organisational construct creates challenges for organising work and resource allocation. The modelling uncertainty present in the organisation aggravates the fight for data as a scarce and protected resource for modelling and for enhancing organisational capability. I identify and explain that as entities and organisations refuse to share data, 'data barriers' exist internally and externally in the organisation. I see this, for example, in the organisational culture of encouraging technological competition for innovation, which reinforces organisational data barriers. In this sense, the realisation of Big Data analytics transcends its material properties. It demands a change in organisational communication and coordination. Neglecting the issue of organising Big Data work leads to an impasse of modelling, which later may result in gamification of the modelling result as a response to cope with the high expectation of technological delivery.

In this section, I present the making of data as an organisational construct. Organisational culture in the tech giant encourages internal competition, and each internal group protects its data as a strategic asset. I argue that the current state of organising Big Data work is making organisational communication and coordination more challenging. Soon after, I offer a glance at the delivery of current analytics technology. Our research shows that technological material properties provide a means for the gamification of data scientists' personal performance evaluation to cope with the complicated organisational environment that impedes Big Data modelling.

### 6.1 Data as an organisational construct

The organisational construct of data access comprises internal and external data sources. Internal data sources encompass all data captured by users' activity on products offered on the tech giant's platform. This data is then connected and enriched, stored into databases, and converted into data that can be used for analytical purposes. External data sources depend on the business and political environment as it relates to accessing data from public registries and data vendors. An agreement providing access to and setting up an application programming interface (API) for enquiring about and transferring data requires organisational coordination and the alignment of commercial interests.

The tech giant researched here possesses a significant amount of proprietary user data, including users' social media data, communication data, payment transaction data, consumption data, gaming data, investment data, and data from various other applications on its platform. However, organisational boundaries and internal structures specify the type of proprietary data the CSC can directly have access to internally. For example, CSC does not have data access to social media or communication data, or other data not generated from applications offered via its payment platform. The CSC belongs to FIB, which manages its payment platform. This organisation's platform stores a vast amount of information related to payment transactions, consumption, and investment, all of which takes place via its payment platform.

Access to external data depends on the political and organisational coordination of interests. In 2016, the PBoC issued a strict policy to supervise payments, requiring all non-bank payment accounts to have a real name and a verification rate of up to 95%. In 2018, the real name verification database comprised 1.9 billion pieces of data from 730 million natural persons. On an average day, this data increases by four million pieces of data, including personal ID information, phone numbers, bank account numbers, and other multi-dimensional data. Following the CSC's new setup, data scientists and project managers within the CSC have sought to affect links to different data sources, both internally and externally. As one project manager stated:

> The nature of credit reporting is to share data… That is, you have to put different data together and make sure that data can be connected with [an unobstructed flow of data communication].

Big Data credit reporting technically arises from negotiating and coordinating in a bid to set up APIs and from constructing the infrastructure needed to make requests and effect communication between different data storage instances. The amount of data involved can be significant, and as such, numerous APIs must be created. However, the extensive scope of personal data items requires a comprehensive data-enquiring mechanism to summon and match an individual's information. To achieve this, following PBoC practice, the personal ID number is used to summon and match individual information. Through matching and effecting communication with a broad scope of stored information related to individuals from different datasets, credit reporting practice can encompass identity authentication as the first step in credit reporting and scoring tasks. This infers that all other information without any indication of personal ID will create problems in terms of data matching. According to one product manager:

> To gain identity authentication, we need to connect to the Ministry of Public Security's database. This is the most authoritative [entity] in the country, because there is a match between all the names and ID cards in China among the household registration population. We then primarily connect to the four major telecommunication carriers…those that have the cooperation of mobile phone companies. We can then connect to…other data, such as information pertaining to driving licenses, among others.

The Ministry of Public Security's database includes identity information that spans the entire Chinese population, including individual ID numbers and names. This basic individual information is sensitive, protected, and generally inaccessible to companies. The reason for CSC having this information is linked to the legitimisation of the credit reporting for the state programme, the result of previous negotiations with the PBoC, and to establish verified real-name accounts in its payment system. Moreover, credit scoring is needed to establish consumer needs to link different public databases to gain identity and other individual information.

In light of datafication, data has become a valuable commodity for strengthening organisational capabilities while at the same time, being protected to ensure personal privacy. This research focuses on the inevitable data boundary that Big Data has as an organisational construct. In this regard, establishing how to gain access to different data sources and datasets and the specific data that should be stored within these sets remains an ongoing issue. In the current case, the CSC has to reach out to the courts, police departments, telecommunications companies, and even railway companies for collaboration to obtain individual records. The CSC adopts a proactive approach to construct access to different external datasets by creating good relationships with the government and other data sources and to gain additional internal access to data via communication and coordination with other internal groups.

### 6.2 Data barriers as a result of managing organisational silos

*Data barriers* refer to the barriers and gaps that exist that limit data sharing. External and internal data barriers prevail for several reasons, e.g., legal and technical (difficult to access, large scale, data storing errors) aspects, and organisational competition and incentives. In this section, we review these coordination obstacles between different organisational silos within the tech giant, all of which impact data barriers.

Technological organisations have noticed the importance of becoming platform-centric, as Yoo et al. (2012) point out that the prevalent usability of digital technology with its extensible, open affordances has emphasised the role of a platform and made it the focal point of organising innovation activities. Likewise, different applications and functions of the tech giant's platform rely on various teams and highly segmented work units. Accordingly, data are also stored in and obtained from different segments within different work units in order to fulfil different functions. In the present case, as organisational structure, work objectives, and incentives become self-oriented and diverse, subsequent organisational silos develop.

Silos, in the organisational literature, is typically employed to describe a lack of desire or motivation for implementing coordination (at worst, even communication) between entities within the same organisation (Serrat, 2007, p. 714). This recognition underscores that structural barriers in large organisations lead to the tendency for work entities to work against one another, which can subsequently develop into data barriers.

For example, the CSC operates within the tech giant’s payment context and within its own silos. Internally, other entities in the organisation have no obligation to share data, and doing so will create additional work for them and distract from their own objectives. In some cases, factions within the same organisation may even believe that sharing individual data will cause the specific division to lose its strategic position within the organisation. According to a modelling supervisor:

> We have barriers to data sharing. This is very common; almost all large companies have them. Also, on the departments from the social media side, they have a lending platform that generates significant profit. Other departments certainly will not want to share their data with us. We have internal competition…other groups do not] share data with us.

In alignment with the affordance to enrich the platform’s functionalities, the tech giant has an internal culture of encouraging competition to boost efficiency. Incentives for each group are set in a bid to further its specific functions, which in turn strengthens silo boundaries. This incentive aims to maximise the performance of each silo. Coordination for data sharing internally between the self-contained silos can be challenging, as it is often difficult to convince different groups to cooperate and share data without reciprocal gain. As a result, these silos create individual frustration related to coordination between different entities. A data scientist shared her jarring experience of negotiating with another group in an effort for them to share data with CSC:

> I understand they see no benefit in sharing their data with us, and that we all have many tasks to complete each day, but I do not understand why data scientists from other groups have such a negative attitude. If they do not want to share data with us, they are free to do so. There is no reason to insult or ignore me. I even invited our director to our chat

> group and asked him to say something [to facilitate the negotiation] but he said nothing in the chat group.

Data sharing is frustrating and challenging, as other organisations and entities will typically not share information without any partnership or resulting benefits due to pre-determined work objectives and incentives within different departments. In the current case, leadership within CSC realised that the challenges and slim chances of achieving internal coordination could be addressed by breaking down the boundaries between different information silos. As such, the CSC places a larger focus on accessing external data.

Externally, in a competing environment with other payment platforms sharing the market, it can be extremely difficult to access all available consumer financial information and behavioural payment data. Nonetheless, CSC can create business cooperation with other credit merchants to obtain new samples of the credit data or data generated through productisation, i.e., by creating a product for consumers. Where this is the case, consumers will generally voluntarily share their data if they are using a product. A product manager stated the following:

> Banks are…conservative organisations within the economy. They are reluctant to share customer data with others. When we cooperate with banks, we anticipate that they will share payment data with us. We use methods to ensure this, such as proposing a product to help them better serve their customers. For example, when I approach banks, I generally engage with their data entry staff… I may receive data about their users' credit card activation to observe whether…customers activate their credit cards following application, and whether customers make their first payment with the newly activated card. In doing so, we can work with…banks to provide users with benefits and rewards. For example, when they use the newly activated credit card

> for the first time, we can refund a percentage of the payment via our payment platform. This was created as a type of product model…to encourage users to spend and consume, and…[to] maintain trust… Following this process, we can then receive details about the data in return.

Productisation appears to be a fundamental aspect of breaking down data barriers. The reason for this is that both enable an approach for linking data in sub-systems that have been devised to enhance different contributing functions when creating a new product synergy, an alignment of interest. However, as a result of organisational structure and the various groups charged with fulfilling a diverse range of functions and goals to realise the platform's complex functionality, organisational silos have arisen within the tech giant. Though organisational silos can create competition among a range of different interests and lead to the segmentation of resources, individual coordination of data will, as a result, become frustrating and challenging.

## 6.3 Technological delivery: Gaming material properties in response to the state of organising

The data scientist's work is organised as a standardised, repetitive, and routinised procedure. This is due to management's trust and belief in current procedures and in deep learning algorithms. This has made model-building more data-driven. However, constant frustration related to expanding data construction as a scarce resource has continued to rise, indicating a level of uncertainty about ensuring modelling predictability. The uncertainty and low performance in model-building create concerns for personal gain. When combined with a somewhat dysfunctional performance measurement regime, this creates problems in actualising technology affordance. Data scientists' personal performance is measured against the credit score model performance because the modelling team's main goal is to enhance credit default prediction. However, how the performance of the credit score model is measured seems to only approximate the latter, in an entirely contestable manner.

What can be considered a good model? According to data scientists, if their models can achieve a high score in the Kolmogorov-Smirnov test (K-S or KS test), it infers that they have created a good model. The main evaluation in CSC for the predictability of a model is based on this test. A KS test can produce a chart for measuring the degree of separation between positive and negative distributions, thereby separating good and bad lending accounts. For example, suppose a KS test score is 100. In that case, the model score can separate the population into two separate groups, in which one group accommodates all the positives and the other all the negatives. Contrastingly, if the model cannot distinguish between positives and negatives, the model will, in effect, select cases randomly from the population (the KS will be 0). In most classification models, the KS test score will be between 0 and 100, and the higher the value, the better the model will be at separating positive and negative cases.

The KS value is the statistical measure of the model's predictability and a materialistic property. This is widely recognised and accepted as the industry standard. Data scientists classify whether a model works well or not via objective and direct observation because they can consider a statistical figure as KS and as a direct materialistic feature since it will be difficult to directly observe whether the model works well in a lending cycle.

> The modelling supervisor advised the director of the CSC when the latter expressed frustration in a weekly meeting upon reviewing the model KS. '[Only] the top-level [management] [has knowledge of the] KS… [The] KS has been [viewed] as the main indicator for evaluating the performance of the model for [a] long [time]. It would not be convincing [to] tell the top level now that [the] KS is not a good measure.

– Fieldnote excerpt

The average KS of the models at the time of observation was roughly 32, and there had been no additional improvements or breakthroughs for three months. The most recent version of the model had a KS of 50. Thus, several meetings were hosted to deliberate how a breakthrough could increase model predictability, given that receiving more internal data is less promising (see the above section). Low morale was observed throughout the team. Data scientists believed that their performance was linked to the model's performance. Individual frustration increased as data scientists' personal performance indicators were linked to the KS score. Conversations often took place, expressing concerns about the KS of models. The fieldnote excerpts below represents a private conversation that occurred between three data scientists:

> The KS of my models are all around 30; my mid-year evaluation will be good. It is possible for me to get a three-star review.
> – Data scientist A

> I changed a set of samples today and my KS rose to 38; it can go up to 50 after additional adjustment. Now, I do not worry about…mid-year evaluation. I thought I was going to get a two-star review for my personal performance evaluation. Previously, the KS of my model was too low.
> – Data scientist B

> In my model, the KS is still low; I suspect the sample from microlending we received was fake.
> – Data scientist C

The measure of KS as a key performance indicator (KPI) for data scientists alters the goal and content of their work and modelling to achieve a high KS on the testing sample, meaning that their work is being measured on the KS score on the testing sample, not on the general model performance in the real lending scenario. This allows possible gaming against a high KS or overfitting of these models. Overfitting a model means adjusting models to capture the noise within sample data, thereby fitting the model to the development sample's data points. In the current case, when the model signals overfitting according to one dataset, it lowers its power of inference when the model is used with another lending dataset. Moreover, if the development example includes errors, in the presence of overfitting, the inference power of the model will be reduced.

In a weekly meeting, the director of CSC suggested to one data scientist merging the KS of two sub-models to report a higher KS:

> The director reviewed the Excel table and glanced at the number 32 in the KS column, blinked, and scratched his head. He…asked the modelling supervisor, who was sitting next to him, in a low voice, "What was the KS of the previous models in the first version of the 2017 scorecard model?" The modelling supervisor answered [that it had been] 50. The director was surprised at this answer and asked, "What do we do now? How can we report to…top management with such a low KS? What should we say?" None of the director's colleagues answered. I noticed that everyone was looking down…or at their phones. Only one colleague was looking at the screen. I looked at the director, who considered everyone else, but no-one returned eye contact with him. Later, the director asked colleagues A and B, who were developing the models, whether they could merge the two separate models. The two colleagues were…confused about what the director meant. The director explained…how [they could go about this and said], "Merge these two models together as if one is the other's sub-model". – Fieldnote excerpt

The above is a case that showing a number as a material property of a model works as an easy and objective signal for measuring work quality instead of reflecting the quality of the technology in production. This changes the original objective of data scientists' work from predicting lending defaults to achieving a high KS. This material property is used as an objective signal to compare work quality. Given that the last version of the model has a KS of 50, the new CSC leader needs to achieve a KS of over 50. Manipulating the material properties of the technology (e.g., by overfitting the models or artificially showing a higher KS) comes as a response to the high expectations of the technology and frustration of coordination in organisational life.

## 7. Discussion and Conclusion

This study's findings pragmatically demonstrate the building procedures of Big Data credit scoring models and the issues and struggles revolving around their relevant constituents, including data, algorithms, outputs, and key performance indicators.

With the belief that machine-learning algorithms can work beyond human imagination and infer predictive relationships for model building, data science work is organised to follow a standardised procedure to prepare data for machine-learning algorithms. The limitation of technological artefacts frames the workflow of data scientists to be continuous and repetitive. In this respect, relying on machine learning algorithms turns highly skilled work into a process of performing routinised tasks. Therefore, the nature of modelling work is constrained in an impasse of deploying existing knowledge of preparing data and running the pre-prescribed codes rather than tinkering and on-the-spot problem-solving.

In this, data scientists have lower control over the modelling work as they do not know how they can improve the model's predictability. Before data scientists build their model, they have no prior assumption and control over what the model would turn out to be. In this sense, data scientists' work demonstrates a high level of uncertainty due to no prior understanding of what can possibly increase model predictability and a high reliance on access to new datasets. In turn, this modelling uncertainty manifests itself in organisational processes, aggravating the fight for data as a scarce and protected resource for modelling.

Our research finds that internal data sharing between departments is frustrating, and resource sharing is limited. This is because the internet company aims to enrich its platform features to actualise their perceived affordance to become platform-centric. Therefore the company separates the functionalities and team objectives between different departments, which reinforces organisational boundaries, makes coordination difficult and thereby creates data barriers.

In general, Zuboff (2019) renders the logic of the accumulation of data for surveillance as a fourth fictional commodity, as coined in the concept of 'surveillance capitalism', 'data capitalism' (West, 2017), or 'platform capitalism' (Srnicek, 2017). In such a light, data becomes a precious asset and can create affordance to penetrate consumers' life, whereby different organisations and different entities refuse to share data. The existence of data barriers, later on, encumbers the predictability of the model and can even exacerbate injustice and discrimination in the model (Williams et al., 2018) or lower predictability of the model.

Data scientists believe that if a model has a high KS, the model is good. As KS is also set as their personal key performance indicator (KPI), I find that data scientists overfit the model or tend to game against it to achieve a higher KS artificially. Overfitting the model increases its power of inference for the dataset upon which was developed and tested but lowers its power of inference when the model is used in a real lending setting. As such, the affordance is motivated by the individual data scientist's KPIs; the data scientist overfits models to reach higher KPIs. This research shows that actualising technological affordance for organisations can cause unintended consequences that the organisation would want to avoid.

In addition, they believe that with ever bigger data, they can build more advanced models, in spite of the fact that they already have a vast amount of proprietary data compared to other companies. However, in this, the notion of affordance is being taken for granted and being pre-determined by the political (the CSC was selected as one of the eight state projects to conduct Big Data credit scoring), the social (the credit models are built based on standard industrial practice), organisational capabilities and their own habitats (the data scientists' educational background and work experience).

Recent research on Socio-materiality (Leonardi, 2011; Wacjcman and Rose, 2011; Orlikowski and Scott, 2008) has focused on the social configuration of materiality on technology in organisations, with the contemporary concerns of the 'dynamic, distributed, and interdependent nature of technologies in use today' (Orlikowski and Scott, 2008, p. 438). In an example of artificial intelligence, affordance is a very important concept to understand the practice of AI in an organisation because how people see affordance will have a direct impact on the technology, such as when people perceive and actualise artificial intelligence, and they will use that to develop their practice further. However, what they see artificial intelligence can do is often shaped by social, political, organisational, and individual factors. Due to the organisational fallibility made evident in this research, there is a clear need for further investigations and insights into the social shaping of technological affordance.

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# III. The Mountains are High and the Emperor is Far Away: Local Rendering of a State Calculative Technology

**Abstract**

Calculative technologies are not solely technical configurations, but also political and organisationally embedded. With this in mind, this paper analyses the innovation involved in devising an acceptable consumer credit reporting technology within the state programme of building a Chinese social credit system. This research uses a governmentality lens to recount the organisational effort of adhering to a state-led programme, while adapting the technology for a purposeful commercial end. There are many challenges at the organisational level when it comes to delivering technology that can fulfil state aspirations. Awareness of these challenges is essential for regulators and those seeking to contribute to policy around calculative technology in the use of algorithms and Big Data while mobilising institutions in a state project. Drawing on interviews with eight companies selected by the Chinese state to carry out its credit scoring programme, ethnographic data with one of these companies and archival data of the state programme, this research articulates the processes behind the creation of such a technology. Particular attention is paid to the linkages and mediation between the development of the technology and state aspirations. I find that in interpreting the state aspiration, organisations conduct sensemaking, strategising and strategic adaptation, insofar as calculative practices manifest as product optimisation. Organisations render local resources and organisational dispositions while innovating technologically, which, as a result, alters the original state programme. I establish the concept of ‘local rendering’ to enhance understanding of the importance of micro- and meso-level adaptations of macro-level programmes, and contribute to governmentality literature on calculative practices and governmentality within the Chinese context.

**Keywords:** Calculative Technology, Calculative Practice, Political Programme, Credit Scoring, Innovation

## 1. Introduction

This paper studies the innovation involved in devising an acceptable consumer credit reporting technology within the state programme of building a Chinese social credit system. Building a state calculative technology involves multi-level innovation that is aligned with the state political rationales. Calculative practice has been discussed as a ‘powerful calculative apparatus’ (Miller and O’Leary, 1994) that mediates the political rationales (Miller and Rose, 1990) permeating consumers’ everyday lives (Jeacle, 2015). Previous accounting literature (Spence, 2010; O’Regan, 2003; Miller 2001; 1990; Neu, 2000; Rose and Miller, 1992; Miller, 1990) has discussed the political power of calculative practices (Miller, 2001) through a governmentality lens (Foucault, 1979) that emphasises political programmes, rationalities and technologies (Rose and Miller, 1992).

Sherman (1993, p. 11) confirms that accounting figures are politically driven and are also the product of a ‘balancing act between important economic, social and political criteria’. Thus, the interrelations between rationalities and calculative technologies, programmes and institutions are much more complex than what can be provided by an elementary translation between these respective pairs (Lemke, 2002). Lemke explains that ‘the difference between the envisioned aims of a programme and its actual effects does not refer to the purity of the programme and the impurity of reality, but to different realities and “heterogenous strategies”’ (p. 9). In other words, the middle-ground implementation is far more complex than a straightforward operation.

The present paper attempts to unravel this complex middle-ground implementation. It situates itself within an ethnographic account of how enterprises selected by the Chinese state respond to and carry out technology development in a state programme of building a social credit system over six years, starting at the beginning of 2014. This paper investigates different organisational processes of creating a credit scoring technology to measure the consumer creditworthiness of the entire population and the execution of the programmatic aspiration. It traces the development of the organisational innovation responses and evaluates the organisational actors' perceived linkages between the aspiration of the political programme and the calculative practice.

This research views credit scoring as a powerful calculative practice: The construction of such calculative technology can invent calculating selves and calculating spaces (Miller, 1992). This study traces how credit scoring as a calculative technology is generated through organisational efforts to render, mediate and implement the state's programmatic aspirations. Jordan et al. (2016) demonstrate that risk matrices are suffused with semantic connotations and analogies, meaning that the matrices produce discourses for their users and should be seen not only as a mathematical measure but also as devices creating symbolic meaning and trust allocation (Jeacle, 2009). As Burton (2008, p. 53) explains, the constant 'synchronization, standardization and responsibilization of individuals', encompassed by all-seeing credit agencies (Langely, 2013), are crucial in shaping normative effects. With different means of surveillance, credit scoring then exercises moral and juridical judgment to distinguish 'good' from 'bad' consumers, moving inexorably towards the subjectification of 'docile bodies' (Foucault, 1977) who repay on time.

In general, as the scale of data escalates, a scoring metric can be constructed through statistical modelling of consumer behaviours (Zuboff, 2019; Fourcade and Healy, 2016), where credit technologies run assessments of the uncertainty in mass-market consumer credit. This introduces the concept of using 'creditworthiness' to denote 'how much money that one can repay and how much money one can get' (Marron, 2007, p. 45). This research contributes to the understanding of specific visual elements of a risk matrix as a calculative inscription (Dambrin and Robson, 2011; Latour, 1987; Quattrone, 2009; Robson, 1992; Swieringa and Weick, 1987). The construction of creditworthiness manifests how much trust the creditor decides to put in one person, depending on the information they have available, i.e., the 'visibility' of a credit applicant.

However, Poon (2013) explains that a credit score is a product of the institutionalisation of a rating agency. Although this 'institutional trust' (Poon, 2013) or the measure of a user's creditworthiness can vary from organisation to organisation and from culture to culture (Jeacle, 2009), determining the ideal measure for the population under examination always generates debate. A calculative practice developed by one organisation under a political programme can be a joint product of many factors (Rose and Miller, 1992). This can be due to the tension between the programmatic demand and the technological implementation (Power, 1997, p.74) and contested rationalities in the implementation process (Espeland, 1998, p. 37).

More broadly, although we know that science and technology can be used to fulfil society's 'grand challenges', how exactly can this be done? How do we mobilise organisations with different resources and objectives to navigate towards the desired outcomes of the state, and how can we make sure the technology succeeds in delivering the grand political aspiration at a distance? Many challenges exist in maintaining technological implementation in line with the political rationale. Conceptually, how does the link between enterprises' calculative technology delivery and the state's political rationale come into being?

This study answers these questions and contributes to the existing literature in two ways. First, we explain how each of the organisations establish their calculative technology differently, while concerted efforts to render their organisational resources and disposition. We find that through sensemaking, strategising and strategic adaptation, the organisational enactment of the discursive and abstract programme subsequently also alters the programme. Second, this research develops a concept of 'local rendering' to highlight the importance of localisation in the meso-level of operation. As Whittington

(2011) notes, 'for accounting, strategy and similar societal practices, practice–theoretic research can never be purely "micro" or "macro"; the other is always present, even if temporarily not center-stage'.

This paper proceeds as follows. First, I review the extant historical accounting literature on calculative technology. Second, I delineate the political context in a particularly transformative era of a debt-fuelled society, in which political rationalities and social norms are designed to pass through the political programme. Third, I explain the organisational process of rendering the programme and its strategic development of technological innovation. In this, I explain the relationship of mutual exchange between political aspiration and technological implementation. Fourth, I describe the current status of how calculative technology is presently performing as product optimisation, where the state's aspirations lead into tangible commercial gains for the organisations. Finally, I present a discussion and conclusion.

## 2. Literature review

### 2.1 State aspiration, political programme and governmentality

Governmentality is important to this study because it conveys the influence of the construction of Big Data credit scoring technology and its attempt to modify behaviour, underpinning the invisible power it carries over consumers. We then use state aspiration in governmentality to evaluate whether the final technology delivers such a result. Governmentality enables us to understand how power is exercised over people and cultivates self-control (Foucault et al., 1991). As such, when one understands that 'the art of government' is to re-define economic activities and redirect the economic and social relations of individual lives (Foucault, 1979), one can begin to understand the goal of the state aspiration.

The governmentality framework assists in understanding the interplay between different levels of analysis. According to Miller and Rose (1990), political rationality is usually integrated and manifested through ‘programmes’ of government. These ‘programmes’ mediate between design rationality and particular practice, technique and technology, passing on beliefs and aspirations. Miller and Rose (1990) also explain that efficiency and productivity stand at a central position in the rationality of the design of calculative programmes (Menicken and Miller, 2012). Efficiency and productivity are then manifested in the calculative practices and technologies of accounting, emerging with the discourse of an efficient nation.

Foucault (1966; 1967; 1977), in his early theoretical framework, noted a converting-power transition from sovereign power to disciplinary power, using a deconstructive approach to illustrate how power is intertwined and erected, and specifically to explain how power is tightly connected to different forms of knowledge (Foucault, 1970). Disciplinary power with relevant knowledge and technology responds to sovereign power to regulate life and determine how to ‘let live’, ultimately managing bodies and life in general. After elucidating the concepts above, Foucault shifted his focus to governmentality (1979). He critically addressed how technology and ‘government’ construct the ‘truth of life’ (Rose, 1999a; Miller, 2001) to guide and govern individual conduct and decision-making, as a ‘conduct of conduct’.

Previous literature has addressed the idea that the engineering of such technology as a ‘conduct of conduct’ makes individual performance visible and calculable in financial terms, such as cost and budgeting (Miller and O’Leary, 1987), for scrutiny and measurement to cope with risks. Moreover, the standardisation and normalisation (Rabinow, 1986) of calculative practices, such as accounting, seamlessly penetrated and transformed individual life through the introduction and production of the immoral (Rose, 1996). Thus, these technologies create a framework and space (Miller and Power, 2013, p. 557) for ‘entrepreneurial choice’ and the ‘responsibilisation’ of subjects who are empowered with regularised liberty to behave themselves (Ferguson and Gupta, 2002, p. 989), consequently transferring the risk onto the individual enterprises (Osborne and Rose, 1999, p. 740).

Individual enterprises have the freedom to come up with unexpected behaviours, detached from normal occurrences. They are enacted and subjectivated to respond to certain technologies.

Accordingly, Miller and O'Leary (1987; 1994) see calculative practices playing important roles in the 'modern apparatus of power', as 'contingent devices, constitutive elements of particular modes of governing economic life' (Miller and O'Leary, 1994, p. 100). Through the discourse of these roles, individuals learn to position themselves as calculative individuals (Rose, 1988) being assessed and evaluated for their productivity and efficiency. This explains why the calculations of the government entered consumers' lives for the first time in the post-Second World War period of the United States, where calculations of the state saw consumers as the primary resource of economic management (May, 1988; Gelpi and Julien-Labruyère, 2000; Jeacle and Walsh, 2002; Cuganesan, 2008; Burton, 2012) to proliferate economic growth and perpetuate consumption – the latter being very much a part of the political rationalities of the day.

### 2.2 The discursive linkage between programme and calculative practice

Accounting scholarship on governmentality has noted the capacity and complexity of the accounting technology (Rose and Miller, 1992, p. 175) in ensuring governance and accountability. However, it has not resolved the problem of the ambiguity that comes along with it. Calculative practices consist of different forms of techniques, such as thoughts, laws, organisation apparatus, reports and registers, and also involve people, such as accountants and auditors. In this case, the complexity brings out ambiguity and interpretive reflexivity that constitutes the 'impotence' of accountability (Radcliffe et al., 2016). Thus, the governmentality research effectively points towards how technologies, or calculative practices, are tied up in the enactment and recursive definition of ambiguous programmes.

The political rationales of the government, programmes and technologies are foregrounded, as they are three intrinsically linked layers. Extant accounting literature has stretched the contour of how programmes are made thinkable and exercisable through calculative practices (Mennicken, 2008). Miller and Rose (1990) give prominence to the complex processes of negotiation and persuasion enacted in the assemblage of loose and mobile networks that reconcile persons, organisations and political objectives into alignment. Miller and Rose (1990, p. 27) argue that the alignment relies upon the expertise in the complex network of the enterprises (Miller and Power, 2013) to line up connections at both the conceptual and practical levels. The complex networks indicate the variance in the contrast of the political rationale of making the nation productive, the attempt of capital owners to maximise their economic gains and the techniques for governing the subject.

Concerns abound in the complex networks and multiple interactions (Provan and Kenis, 2008; Provan and Milward, 2001) that experts' knowledge can give rise to enclosures in many aspects (Rose and Miller, 1992). This means that experts can bind and link the operation of the network through their arguments and calculations to exercise power – a negative effect that contributes to the intensification of reliance on judgment and experts' power. Critically, Kurunmäki and Miller (2011) show that experts' ideas and judgments can be asymmetrical and misaligned, where the operating technology and instrument can be blended with competing ideas. As Rose and Miller (1992, p. 190) describe, technologies create unanticipated problems at the operational level, where the technical conditions cannot fulfil its need.

Meanwhile, as the programmes are discursive and ambiguous, the interrelationship between these three layers is far more complicated than an explicit top-down and straightforward system. Accordingly, studies (Miller, 1986; Miller and O'Leary, 1994; Rose and Miller, 1992; Mennicken, 2008; Spence and Rinaldi, 2014) have noted that rationales and programmes can miscarry and fall short. For example, Spence's (2010) study on how accounting as a calculative practice was used to forge the union of the

Scottish and English Parliamentarians in 1707 shows that the technical condition of the calculative system may not be able to fulfil the grand political rationality, while in practice, sub-programmes are necessary to serve the technology, instead of the technology staying principally obedient to the programme.

Moreover, Ahrens et al. (2020) demonstrate the concurrent programmes between different spaces and different levels of governments, which result in conflicts of results and ‘counter-conducts’. As alignments of rationales, programmes and technologies are not usually robustly fitting, they call for an examination of the effect of the competitive and local level of rationales. This study suggests the absence of counter-rationales in the government as regards the governmentality, which points to the importance of looking at the possible contrast and variance between the macro-level rationales and local rationales in the public and private sectors.

Besides, the operation of calculative practices is always situated in an enterprise’s organisational context (Jeacle, 2015; McKinlay et al., 2010; Miller and O’Leary, 2007). In studying programmatic corporate reform, Carter et al. (2020) analyse the role of leadership in realising and stabilising changes in calculative practices, as power was accompanied by conflict and resistance (Apostol, 2015; Clegg et al., 2006). This elicits the question of agency on the meso-level, in which the corporate leader was embodied as a significant part of the programme for the attainment of the objectives. This result adds a meso-level factor into the consideration of implementing and comprising calculative practices in the enterprises. For this reason, calculative practices should be considered as a co-constructed product of the political programme and meso-level actors, and many more meso-level factors should be taken into consideration.

From the above, researchers’ explanation of the decreasing calculative complex fall into two camps—the discursive programme and technical conditions for implementing its use, and the tightening efforts to examine how the link is being implanted and constructed in the meso-level of innovation to explain how the 'mediation'[2] in the accounting complex has been developed. Specifically, when I conduct an ethnographic account of governmentality research where programmatic aspiration remains far more distanced, the nuanced interaction and linkage between the local enterprise actors and the programme line can be teased out.

## 3. Data and methodology

> [Language] once emancipated from the specializations of the understanding it would be able to express the movement and temporality of life (Foucault, 1966, p. 332).

Foucault (1966) explains that language and discourse are a comparatively stable and spatially diverse system of knowledge derived from the nuanced meanings of objects of knowledge (as shown in the quote above). Hence, discourse entails the knowledge that is obtained through the social meaning generated within its own temporality and space. To guide his analysis of historical reconstruction, Foucault (1979) manoeuvres the concept of 'governmentality' as a 'guideline' (Foucault, 1997, p. 67). He explains governing (*gouverner*) using modes of thought (*mentalité*), which implies that the study of the technologies of power demands a deeper understanding of the political rationality underpinning them (Lemke, 2002). Considering the awareness of discourse and the attention paid to it, this study seeks to use Foucault's concepts to understand the administrative power of the regulators and the political programme set by the State Council that was transmitted through the discourse that they created.

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[2]Mediation is the means through which connection is made with other spheres: 'it links up different actors with a common narrative and may constitute a net- work of relations within and beyond the boundaries of the enterprise' (Miller and Power, 2013, p. 562).

### 3.1 Data collection

This study collected and conducted an extensive review of archive documents from 2013 to 2019 issued by the state and regulators, as well as the coverage by the Chinese state media, to understand the constellation of the technologies the state attempts to achieve.

To untangle the middle-level relationship and implementation of the organisational practice measuring creditworthiness, 25 semi-structured interviews (each lasting up to 50 mins) were conducted between 2017 and 2019. The author conducted interviews with senior managers, model developers and product managers in the selected organisations to understand the organisational contexts and their design and how they built their credit reporting technology. These interviews revolved around their organisational understanding of the state programme and their organisational processes in which they gradually shaped their credit-scoring models and technology. Through these interviews, the author sought to understand the norms and customs of development teams and how the reconciliation of all complex factors is facilitated within organisations' operations.

More detailed data was sourced from the researcher's 695 hours of ethnographic fieldwork as part of the data modelling team in one of the selected companies from May to August 2017. Geertz (1983, p. 119) emphasises that the ethnographic field, in reality, is 'insistent' on its specific logic of functioning. Regarding fundamental reflexivity (Hammersley and Atkinson, 1983), when the author was immersed in the field (Czarniawska, 2007, p. 7) as a novice in the organisation, the author could articulate surprises through the organisational logic and practices that were taken for granted. During the observation period, the author kept a daily research diary, incorporating detailed fieldnotes for every day at work and off work, generating 469 pages of fieldnotes and 15 two-hour meeting transcripts, complemented with semi-structured interviews adding up to 24 hours of recorded audio material at the end of the ethnographic observation. The author further worked with the selected company's director and participated in a research project appointed by the Chinese National Internet Finance Association (NIFA) focused on setting the standard of personal credit information collection for credit reporting.

### 3.2 Data analysis

To understand the phenomenon, the author first reconstructs a detailed chronology of events for the project development and the political agenda of building a social credit system, including the regulatory notices, regulatory meetings and the foundation and development of each organisation. The author tracked changes in activities, performance and regulatory requirements. The purpose of this step is to understand the sequence of events and see how the different selected companies responded to and changed their innovation to cope with the evolving regulatory agenda. The author built a track record of the series of events taken place and constantly updated the historical development of each case as the study progressed.

With the collected data, the author then examines and sorts the data in relation to the research question (Ahrens and Chapman, 2006). The data analysis of this paper is afterwards guided by the approach of Gioia et al. (2012). To preserve the rigour of qualitative research and the originality and utility of the phenomenon (Corley and Gioia, 2011), this paper conducts a systematic analysis of the data in parallel to perform informed theory building and theory testing.

Our systematic interrogation of the data first consists of a systematic 'first-order code analysis' and a 'second-order analysis'. The first-order code came from the informant's very own words and terms. The second-order analysis came from the author examining the stack of intact first-order codes and investigating the implications of the codes. The author then set out the analysis by aggregating the 'first-order' codes into certain categories and trying to understand the meaning that these groups of data were trying to convey conceptually.

Meanwhile, the author iterated back and forth between the data and the emerging codes (Strauss and Corbin, 1998; Suddaby, 2006), until the generated second-order could summarise and explain the first-order codes. The second layer codes are the intuitive features coming from the first-order codes, which conclude the trajectory of movements and actions of the different organisations in relation to the implementation of the state project. Furthermore, the author brought the second-order code back to the governmentality framework to explore the theoretical possibilities (Gioia et al., 2012, p. 23) for theoretical development. Multiple iterations (Locke et al., 2020) of the same process took place before the author reached the codes that allowed the phenomenon to be understood. The third layer codes become subtitle five and subtitle six in this paper for analysis, and they assist in the understanding of the phenomenon.

## 4. The state programme of building a social credit system, 2014–2020

### 4.1 Programmatic aspiration: cultivating a trustworthy society

> China is currently at a critical stage for deepening economic system reforms and improving the socialist market economy system. The modern market economy is a credit and trust economy, and establishing and completing a social credit system is an important step in rectifying and regulating the market economy order, improving the market's credit environment, reducing transaction costs, and preventing economic risk (The Chinese State Council, 2014).

On 14 June 2014, the Chinese State Council announced a detailed plan to construct a social credit system. It highlighted that the general concept of constructing a social credit system was a response to the need for deepening market reform. The above quote is the first section of the 2014–2020 construction plan for a social credit system. The plan set requirements for building a social credit system as ‘an important method to perfect the socialist market economy system’ and, as a result, to ‘accelerate and innovate social governance’. By building a social credit system, the state council sought to achieve its political rationale of perfecting its economic system, in which it aimed to reach satisfactory social governance, i.e. ‘raising the honest mentality and credit levels of the entire society’.

The necessity of such a programme was explained in detail in another document: *Opinions of the General Office of the State Council Concerning the Building of a Social Credit System* (The Chinese State Council, 2007). The document states that the construction of the social credit system is reckoned to be the solution to a series of grim economic misconducts, such as ‘malicious arrears and fleeing bank debts, swindling and evading taxes, commercial fraud, production and sale of counterfeit goods, illegal fundraising and other such phenomena’ that ‘cannot be stopped despite repeated bans’ (The Chinese State Council, 2007).

The aforementioned discredited behaviours are perceived as constituting a high risk for the financial market. The overall level of loans shows a steady upward trajectory of 14%, on average (Table 1). Since 2011, internet finance in China has increased substantially. Various internet financial applications now provide non-bank credit suppliers with platforms to extend loans to small enterprises on a larger scale, and peer-to-peer lending has developed rapidly. The growth of these new kinds of credit services necessitates an effective risk management framework to support them. In particular, internet finance takes applications and automatically approves loans online, which depends upon the risk management of verifying and auditing consumers through other available data. Internet finance thus casts a higher risk of exposure for lenders due to information asymmetry (Xinhua, 2016).

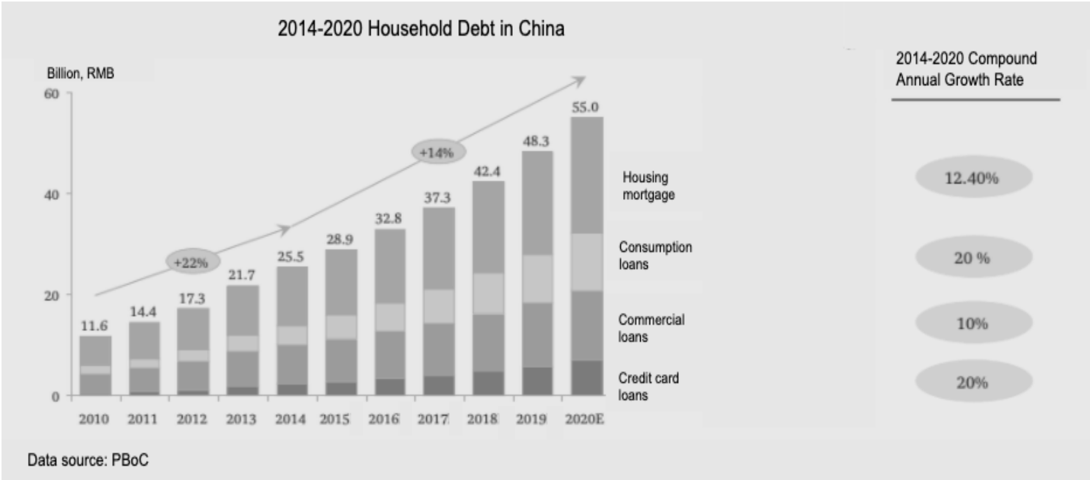



Table 1: Household debt growth in China

Accordingly, a series of discreditable, trust-breaking behaviours, such as internet borrowers running away from their liabilities in 2015, drew the government's attention (People's Bank of China [PBoC], 2015). Table 2 shows the number of cases. At that time, less than 15% of online credit providers had set up information communication of credit data enquiries and connected to the central bank credit reporting centre, meaning that the defaulters were not captured in the central credit registry.

| Year | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|
| Number of P2P platforms that went bust or were found to be problematic | 76 | 395 | 1686 | 3407 | 4219 | 5417 | 5433 |
| Outstanding P2P loans | 2.64 | 6.84 | 16.79 | 26.59 | 33.24 | 176.65 | 177.21 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| involved (RMB billion) | | | | | | | |

Table 2: The number of cases of peer-to-peer (P2P) platforms found bust. Source: Wdzj.com

It was within this context that the State Council believed that the construction of a social credit system was the solution to re-direct economic and social order. The State Council set a timeline with objectives for the social credit system:

> By 2020, there should be established laws, regulations, and standards for social credit; A credit information system that covers the entire society; Sound credit supervision and management systems to cultivate a social credit service market; Enforcement of reward and penalty mechanisms for keeping and breaching trust and raising a stronger awareness of creditworthiness and trustworthiness across society, most of all, a significant improvement in the economic and social order (The Chinese State Council, 2014).

The objectives of the social credit system above rely upon creating assemblages of technologies, including laws, regulations and standards, and a completed credit supervision and management system, that is, a calculative technology that will give rise to mechanisms that cover the credit market. Meanwhile, the objectives require different types of technologies that work together and aggregate to achieve the same government rationale. In turn, this means the political aims and the different levels of diverse actors across the multifaceted efforts to set up different technologies need to be aligned.

### 4.2 How the programme was implemented in progress

The State Council set the overall plan and the objective of this programme. It called for government bodies across different levels of the hierarchy and commercial organisations to take up their responsibility to contribute to the plan. On 16 December 2014, the People’s Bank of China (PBoC) and the China Development and Reform Commission (CDRC) jointly issued a work plan from 2014–2016 for constructing the social credit system. They asked local governments and related institutions to respond to the government’s agenda. The document below also specified that these two authorities would be leading this programme.

> PBoC (Mainly) and CDRC (Secondly) will lead in promoting credit reporting agencies to provide professional credit reporting services and lawfully and orderly advance credit service product innovation...CDRC (Mainly) and PBoC (Secondly) are responsible for leading and improving the sharing cooperation mechanism of credit information, using existing credit information system infrastructure to promote the interconnection of credit information systems and the exchange and sharing of credit information in accordance with the law and gradually incorporate financial, industrial and commercial registration, tax payment, and traffic violations (PBoC and CDRC, 2014, p.4).

The PBoC and CDRC have led the implementation of the social credit system. Together, these two authorities work on the same objectives but have distinctive tasks. The PBoC was responsible for taking the lead for building the technology to serve the financial credit system. This later led them to focus on the establishment of credit reporting agencies to collect and process credit information lawfully. In contrast, the CDRC advocated for collecting and sharing behavioural information across different areas and platforms and setting up constraints and punishments for individuals with misconduct records.

However, this division of responsibilities led to further distinctive opinions in the programme implementation; the PBoC preferred credit agencies using only financial data to denote creditworthiness, while the CDRC favoured aggregating personal information. This divergence in opinion resulted in difficulties in having a clear-cut definition of credit reporting technology and, subsequently, its implementation.

On 15 January 2015, the PBoC issued a document called *About Preparing to Conduct Credit Reporting Business*, stating that 'the eight companies mentioned in the document should be preparing to carry out credit reporting business. Their preparation time to commence activities is six months. The eight companies (see Appendix I) need to comply with *The Regulation on the Credit Reporting Industry*'. This notice complied with the notion of cultivating social credit reporting agencies as an important measure for implementing principles and policies of the Central Committee party and the state council.

Given the above, the PBoC issued a test licence to eight companies that they selected based on applications and asked them to comply with the central bank's guidelines for conducting credit reporting services. The PBoC did not leave the companies with any detailed instructions on how to operationalise this in practice. However, the test license was different from the official license, representing an opportunity to prove one's worth of being granted the latter. For the public and private sectors, this period marked a high point of expectations for the market value of the final license and for being part of a national social credit system.

The above document shows that the PBoC followed the State Council's plan to bring more credit agencies into the market to construct a social credit system. The establishment of the state agenda created a space to summon operational efforts and escalating contributions from different institutions across various levels to concretise and fulfil the programmatic aspiration. There is evidence that many private companies joined the business of providing consumer data and related services and registered their company name with *zhengxin* (meaning ‘to accumulate trust’ or ‘credibility’) in it. More companies applied for the credit reporting license after the notice at the beginning of 2016. This notice also signalled that credit reporting services in China had entered a stage of marketisation, as credit reporting was allowed to be carried out by the private sector for the first time.

Meanwhile, the programme only delineated the main objectives, which left much room for interpretation of actual operational details. The PBoC stated in the notice that the companies who had the test license needed to conduct credit reporting lawfully. However, at that time, the only available resource was *The Regulation on the Credit Reporting Industry* issued in 2013, which specified the condition that credit reporting businesses should exclude personal data, such as religious belief, gender, fingerprints, blood type, disease and medical history, income and any other information prohibited by laws and regulations.

With the emergence of Big Data and credit reporting, stricter requirements were placed on improving the legal system of data protection. Furthermore, laws that clarify the core issues of each subject’s obligation to protect information security and the desensitisation standards of personal information, such as the *Cyber Security Law*, were not issued until June 2017. Therefore, further introduction of laws and regulation of data protection has set up different requirements with which Big Data technology must comply.

## 5. Local rendering influencing the calculative practice

The present study ethnographically explored the organisational process of developing state technology after receiving a test license. There is evidence of innovative technology development in the organisational process of sensemaking and strategic adaptation after commercial organisations were selected to deliver the state technology.

The sections below assert that the concept of local rendering is essential for understanding the empirical phenomena encountered. After being selected as test license companies, organisations exercised sensemaking to understand the programme and performed strategic adaptations to set out the project. I find that local resources and local dispositions played an important role in navigating the technology development. More specifically, organisations' attempts to seek viable technological development were deeply rooted in the *realpolitik* of balancing stakeholders' needs.

In essence, the organisational process of sensemaking, strategising and strategically adapting emphasised rendering the programme from the standpoint of their local resources and organisational dispositions. The organisational understanding of the programme was conceived in a way that was integrated with existing organisational capabilities and local resources. Furthermore, as is shown below, organisations repurposed the technology to fulfil and adapt to their stakeholders' needs and maximise their business value. Conceptually, I argue that the understanding and the actions that took place at the organisations' meso-levels led to a significant alteration of the programme from the original political rationale as articulated by state agencies.

### 5.1 Sensemaking

In coping with the notice of having to prepare to conduct credit reporting in six months and the disruption involved in establishing a credit reporting business, the eight companies demonstrated a process of sensemaking to 'structure the unknown' (Waterman, 1990, p. 41). The unknown gave rise to the fact that credit scoring was still a foreign concept to the companies. The companies were unclear on what the central bank aimed to achieve with the technology they needed to deliver. They did not know whether they would be issued the final official license, what type of data could be used for credit scoring or how creditworthiness would be understood. Further understanding of credit reporting was awaiting development.

By examining the process of technology creation, I identified that our interviewees described their motivation for technology development in a ‘frame of reference’ (Cantril, 1941, p. 20; Weick, 1995, p. 4). As Starbuck and Milliken (1988, p. 51) explain, when people refer to one stimulus point, it enables them to ‘comprehend, understand, explain, attribute, extrapolate and predict’ so that they can heuristically answer the uncharted question of how to proceed with the development of credit scoring. Likewise, all of our interviewees demonstrated a reference point that guided their interpretations. Our interviewees used the programme content and license as a reference point and an impetus to stimulate making sense of how to build the credit scoring technology required by the state.

In particular, companies set out their understandings from their perspectives on why they had been selected as test companies and attached meanings to develop their explanations. Depending on their condition, they inferred that they were chosen because of their expertise or experience in credit assessment or their abundant consumer data resources.

For example, the product manager of Company 6 stated, ‘The PBoC gives us the test license because we have a strong background and experience in credit reporting, thereby we for sure have our advantages’. Company 6 has been running various rating businesses in China since 1992, such as corporate bond rating, short-term financing bond rating, medium-term note rating and convertible bond rating. To substantiate their strong background, the product manager explained further that Moody’s (one of the Big Three credit rating agencies) owns 49% of the Company 6 shares.

Another example is Company 3 It is a subsidiary of Lakala Payment Co., which was the first and biggest third-party payment company before Alipay and Wepay were widely used. The product manager of Company 3 said, ‘the reason we got the test licence is not because the PBoC values our funding capital but because of our data accumulation. Lakala has ten years of third-party payment data, so you can imagine how much data we have accumulated'.

Moreover, companies developed understandings of why they were chosen for the test license in conjunction with the idea of creditworthiness pertaining to their disposition, best interests and already-held beliefs. For instance:

> Company 7 has a long history of working with banks and financial institutions. We believe that credit scoring should solely use financial data and be used in the financial domain. We only use financial data in our model.
> — Product manager from Company 7.

> The innovative part of developing a wider use-case for credit scoring for daily life and using unrestricted data in the finance domain is actually coming from our Chief. It is his belief to make running a business easy as developing trust is crucial. This is coming from the DNA of our large internet company. What he wants to do is let people from all walks of life use this credit scoring service, especially the underbanked people.
> — Product manager from Company 5.

The different understandings of creditworthiness above were linked to the organisations' strengths and already-held beliefs. In the process of finding out what the technology should be like, organisations made sense of their prevailing situation of receiving the test license based on their existing capabilities and resources.

In this situation, Qianhan has more connections and resources in the financial industry. At the same time, Company 5 belongs to a large internet company, whose payment platform has data for more than 700 million Chinese consumers and already possesses vast quantities of consumption data, behaviour data and rental service data. Thus, these organisations subsequently established their distinct understandings of creditworthiness in the context of their existing resources and beliefs. These micro details and technology configurations can be seen as co-products of the macro-level programmatic aspirations and the meso-level organisational renderings of local resources.

### 5.2 Strategising

Companies saw the license as a strategic business opportunity. They aimed to use the license to develop credit scoring technology to complement their platform functionality, enhance their service value or create a profitable business for putting out their credit reporting. They highlighted the importance of getting the licence, as it would help them obtain strategic resources in the form of more consumer data.

Organisations with less data from their systems had difficulties forming credit scoring models in the beginning. Therefore, they contacted other organisations and data vendors to acquire different datasets and commercialise them. The license permitted them to become an intermediary in the market to sell intelligence about consumers, for example, to provide the information about credit applicants' educational background, identity verification and whether the applicant has loans on various credit provider platforms. This business has a high value due to the growing needs of internet lenders.

> One part of credit scoring is consumer data; the other part is credit modelling. But these lenders can only get some data through a Zhengxin company (credit reporting) to assess a credit applicant – perhaps to check one's education certificate. But when this person applied for the credit, this person only submitted his name and ID. While we, as a Zhengxin company, can legally output this data. In the beginning, we were selling data.
> — Product manager from Company 6.

However, the propensity of large internet companies such as Company 4 and Company 5 was to use the license as a means to serve their organisational and platform needs. Company 4 and Company 5 saw an opportunity to develop credit scoring as a vital module to integrate into their platforms. The Company 4 product manager pinpointed that the credit scoring module that they developed helped select and match their users to third-party digital merchants for services integrated with their payment platform.

Above all, these organisations used the opportunities that the test license represented to enhance their capabilities and, therefore, market position:

> Because we all can see, at least in the near future and especially in such a Big Data era, in most cases, if you have data and collect data in hand and can work on them a bit, at least to a point, you can output something valuable.
> — Product manager from Company 4.

The above statement is rather general, but it shows a shared prospect of how product managers recognise the value in abundant consumer data sources. The technique of modelling or building any kind of analytical capabilities is highly dependent on whether companies have specific data for understanding consumer behaviour or generating useful analytics for the business. As a result, a product manager links the ability to collect data with the enhancing capability of delivering useful analytics in the future.

Strategic capability consists of bundling resources and knowledge to reach a unique position in the market (Porter, 1980; 1985). Here, consumer data is the key resource and asset for technology development. By having more data for modelling, the modelling teams could select variables that better detect default possibilities, providing knowledge of what to later include in the model and how to denote creditworthiness. As such, the organisations' capabilities evolved while learning what data correlated with creditworthiness and how to bring value to clients.

However, the data shows that companies strategised from the data sources they possessed and were highly dependent on them. These companies had different starting points based on their access to the accumulation of consumer data. For example, large internet companies, such as Company 5 and Company 4, shared the advantage of having massive quantities of consumer data, as mentioned in the last section. They used their local organisational resources—either in-house, proprietary data or data from merchants and datasets with whom they worked.

| Different levels of data resources | Quotes | Interpretation |
|---|---|---|
| Company 4 has lending behaviour data (from their lending product and lending partners) and proprietary data, such as social network data | Company 4 is more competent in the domain of social media. This is easy to understand as we look at creditworthiness through understanding and digging into users' social networks and relationships. For example, on the list of my friends, I get 100 good friends on my WeChat or QQ platform. Then, none of these 100 good friends has been listed on any blacklist or the blacklisted industry. Then, this user may be a good user. More | Company 4 has data in the form of social network communication. In this case, they can trace the red pocket payment transactions between different friends and abnormal behaviour. They used the concept of homophily to ascertain creditworthiness. |

| | | |
|---|---|---|
| | extremely, if we say that all of your friends are like such individuals (on the blacklist), then we can ascertain that you must be one of such users (Company 4 product manager). | |
| Company 5 has lending behaviour data from their lending product and vast proprietary data from e-commerce, Taobao payment | We launched our credit score in January 2015. We use our proprietary data, including consumption data, personal connection and characteristics, etc., to develop our model. For example, one of the derived variables can be the number of times a borrower has not paid or delivered goods in the Taobao e-commerce ( Company 5 credit product manager). | Company 5 used consumer data Taobao collected on its e-commerce platform and also payment and other behavioural data acquired through Alipay. |
| Company 6 does not have any source of accumulated data. But they have experience in conducting financial rating business; they | We connected with telecommunication companies. We had consumers' telecommunication data. We find it very useful for | Company 6 worked with data vendors who collect consumer characteristic data. They found certain data |

| | | |
|---|---|---|
| connect with lenders and see what data the lenders find useful. | credit reporting because now if you purchase something online, it is all through your phone or registered with your phone number. We have telecommunication data; we can see how long someone has been using that phone, their average phone bill and, also, its active IP location. These are variables that we have found to have some connection to creditworthiness (Company 6 product manager). | useful for judging creditworthiness. |
| Company 8 has no in-house data with which to build credit models, therefore, they focus on negotiating access with lenders to share default data and build a platform | We didn't have any in-house data to begin with. What we are doing now is building a platform to bring all of the microlenders' (similar to payday loans) defaulted data together so they can benefit from each other's blacklisted clients and do not lend to those applicants. And | They acknowledge the fact that they did not have data with which to build credit scoring. They focused on services that can gain usefulness and value by inviting different lenders to share defaulted data and are building a system to give alerts about suspicious |

| | | |
|---|---|---|
| | probably later on, when we accumulate more data, we can run some models, but we have not reached that stage yet (Company 8 product manager). | borrowing behaviour. |

Table 3: Quotes show the different situations and starting points for four of the eight companies

The Table 3 above shows the different situations and starting points for four of the eight companies. These quotes (middle column) reveal the different starting points of their data resources (left column). The companies with both historical lending data and proprietary data about consumers had the advantage of knowing more aspects of the consumer and had more relevant data with which to explore and build credit reporting models. These companies strategised and took advantage of their strengths and weaknesses in relation to their data possession and connection. The data starting point determined the direction of the development of their credit reporting technology (right column) and how they understood consumers and examined their creditworthiness.

We can see that the significance of heterogeneity in organisational resources acts as a basis for competitive advantage and draws a distinction between the organisations. Companies strategised about what data and other resources they had and aimed to capitalise on their advantages. The strategising in the technology development process depended highly on the organisation's disposition, which later distinguished the technologies that the companies delivered.

The attached meaning and strategy related to the stimuli of the programme and the issued license were explained as being due to an endogenous cause. The linkage between the programme and technology was made through ‘expertise’ (Miller and Rose, 1999), represented here by the organisations. Meanwhile, how the technology seeks to operate was geared towards difficulties in rendering their resources and dispositions in the strategising process.

### 5.3 Strategic adaptation

Our data shows that there was a proactive move of strategic adaptation in the wake of sensemaking and strategising. Through adapting the government programme to their operational vision, organisations configured the technology design to their strategic fit. They aligned the goals of the organisation and those of the government programme, where the patterns of technology development arose.

> In China, when we talk about credit, very often we cannot differentiate between credit and integrity. When you default, you borrow money from the bank and do not repay it. We think there are two forms of default; one is the *willingness* to pay back the money, and the other is your ability to pay back. Some people have money but do not want to pay it back. In this case, integrity is highly related to one’s willingness to pay the money back.
> — Director from Company 4

A definition of ‘credit’ that encompasses ambiguity in the programme invites adaptation. The definition was adapted to match a company’s resources and strengths and explain the fact that they were using non-financial and consumer characteristic data in credit scoring, making it different from traditional credit scoring, which uses only financial data. The part that measures integrity and willingness normally comes from data in the life service domain, such as whether consumers return a borrowed bike, whereas the part about creditworthiness comes through the financial domain. The companies wanted to transform credit scoring from restricted calculative practices.

> In our internet company's genetic makeup, we would like to cut the cost of trust between the merchant and the users. With this, we would like to extend the service to non-financial areas. We have a theory that we need to consider how to lower our customer acquisition cost and to raise the user retention level.
> — Company 5 Credit product manager.

This quotation hints at the importance of adapting the government programme to fit Company 5's strategic vision. They wanted to use the programme as a stepping-stone to implement their organisational vision of cutting the cost of trust between merchant and consumer. In this case, the company instilled their organisational beliefs in the social credit system framework. They structured their operations in such a way that they accommodated the programme's aspirations. As the preceding analysis suggests, there was a disparity between the state programme and the organisational operations, contrasting the societal effect with the commercial reality.

> The social credit system wants to promote stronger awareness of creditworthiness in the entire society; we as product managers want to think about helping create more privileges for our score that our users can benefit from, for example, creating benefits in using our service in banking and other daily life. That is to gain more advantages for our users through a credit score.
> — Product manager from Company 4.

This line of argument shows the change of emphasis from the programme to the wider use of the credit score data held by the company. This goal change exceeded the requirements of the state programme while directing the technology to their business benefit. The local adaptation posed a formidable challenge to passing political aspirations to the technology intended to make those aspirations a reality.

In summary, this paper finds that sensemaking, strategising and strategic adaptation are a reciprocally recurring cycle throughout technology development. Companies experiment with different datasets and discuss with different stakeholders and adjust their credit scoring model accordingly. Then, these three activities—sensemaking of the situation with the central bank and the current situation, strategising how companies can find a strategic fit of their business and strategic adaptation—take place again in the cycle of adjusting the models. It shows this process in detail in the next section, where I discuss balancing stakeholders' needs throughout the technology development cycle.

**Adaptation to both the central bank's and clients' needs**

The primary concern for the eight companies was not only the central bank but also their clients. The companies adjusted the credit scoring model to respond to the needs of the central bank. For that, they co-created models with the lenders and constantly met with the central bank. However, the staffers on the frontline were more concerned about maintaining customer satisfaction; the service that their technology provided could help accomplish better risk management of denoting defaults. As a result, I see that balancing the needs not only of the PBoC but also their clients was an important part of companies' motivations for adjusting their credit reporting business and credit scoring technology and was perhaps a process that the architects of the programme did not anticipate.

As the technology was still experimental, it faced several challenges. First, its wide deployment was contingent on the central bank accepting an appropriate credit score. Second, clients needed to accept the technology. Technological evolution depends upon the continued experiments of trying different data and use-cases and obtaining feedback from the stakeholders. One interviewee described technology development as a recurring cycle of attending to different stakeholders:

> It takes a long time of experimenting, working with lenders, judging the market and basing the market response to know which data is needed and which data is not necessary. We have also been through a long period of discussion with the PBoC to reach the current status of knowing that our credit reporting is operationalised in three dimensions.
> — Product manager from Company 1.

In sharpening their credit scoring models, companies experimented with the technology and blended the various data that they could find to meet the needs of lenders. In the refining stage, companies needed to find the measure that worked, so they constantly turned to the lenders, i.e., their clients, to see what they wanted. Also, in this stage, the companies wanted to test and talk to the central bank to see if they liked the measure or not. As stated above by the product manager, these companies looked at the market needs to decide what to offer in the market while under the guidance of the central bank.

The companies went through several rounds of making sense of the central bank's comments, strategising what they could do for a strategic fit and adapting to it. They finally settled their credit reporting product, comprising what forms of data to include in their models and how they decided to set out their credit reporting service:

> The first dimension is similar to this anti-fraud risk control service. Yes, because the demand for this type of market is relatively strong now. Then, the second category is the establishment of a social credit information system. Then, the third category is the sharing of credit and information services. It is these three aspects of task classification. These categories gradually come into being and are led by the back and forth discussion we have with the central bank.
> — Product manager from Beijing Sinoway Credit Bureau.

These companies worked with lenders to use their data to train their models further and learned to recognise whether their measure worked in lowering borrowing risk by using data from whoever adopted the credit score. On that basis, these companies learned what would work well in a model to differentiate good borrowers from bad borrowers based on their local merchants’ data, which constituted the later iteration of the models.

> We want to make sure that the clients who use our service find our product useful. That’s when they will keep using our product.
> — Product manager from Zhong Zhicheng.

> In fact, the biggest challenge we see is to help merchants greatly reduce their cost. We want our merchants to find our score useful for their own risk management.
> — Product manager from Company 5.

Maintaining customer satisfaction is one of the aspects that concern companies. Organisations who develop on the front line need to be able to build a business out of it to maintain the relationship and confidence of their users. Otherwise, the business will not resonate with them, and the state goal will not be achieved, as their buy-in to the idea is required to execute it. Therefore, the development of the credit report modelling used local resources, relationships and local beliefs.

## 6. Calculative practice in the context of ever-expanding product optimisation

> To govern humans is not to crush their capability to act but to acknowledge it and to utilise it for one’s objective (Rose, 1999b, p. 4).

### 6.1 Product optimisation

Rather than building technology that implemented the programme, practitioners used the programme to build products that reflected their strategic visions. Practitioners used the language of creating products instead of building technology.

> We have created different products to serve our clients, for example, ID verification. We provide facial recognition as the first step for our lenders to verify credit applicants. The second step is verifying their phone and address, and the third step is credit scoring – we provide a credit score.
> — Product manager from Company 5.

The change from creating technology to creating products emphasised the product as an instrument to accommodate users' needs and achieve commercial success. With that, product optimisation took place through activities such as expanding use-cases, continual credit model updating and bringing underlying calculative logics closer to business applications, which, in turn, created an ever-expanding data-invasive technology.

For example, the first credit reporting technology among the eight companies that was launched in the market was developed by Company 5. It was first introduced to consumers in 2015. Because of Company 5's ever-expanding use-cases, consumers shortly found that a good Company 5 score was a very useful tool to broaden and empower their life choices. Company 5 scores quickly became widely used and had a significant impact on users' daily lives.

At that time, a Chinese citizen with a Company 5 credit score above 550 could take a bus ride and pay for it later, which saved time when commuting to work during rush hours. A tenant who was looking for a new apartment could check for available properties on the Alipay platform, which uses Company 5 credit scores, allowing the tenant to take advantage of their Company 5 credit score and rent a place without a deposit. A person holding a Company 5 credit score of 650 had 3500 RMB spending credit. Furthermore, he or she could use the credit for food delivery or grocery shopping on their digital platform and pay back the money one month later.

The above is an example of expanding use-cases through product optimisation to make their credit score even more useful. Based on the core credit scoring result, Company 5 created products that could be tied to their score by connecting third-party merchants to the platform.

Credit scoring teams continually incorporated more data from these daily services to re-train and update their models. They used the data generated from product usage to train models for higher predictability. This shows that product optimisation aimed to continue expanding the use of consumer data for better model performance. Productisation was emphasised as a way to gain more consumer data:

> Traditional banks are reluctant to share borrowers' data. We, therefore, work with the bank by creating products for serving the bank's consumers through our platform. For example, we work with the bank to provide service for their credit applicants: if their credit applicants repay their credit card debts, we will give them some kind of reward. Thereby, I proceed in such a way and through the rule of productization. So, this is how to collect data from banks through productization.
> — Product manager from Company 4.

Credit scoring can be the basis for many different products, each with their own logic for calculating and using the score. Likewise, generating an equivalent calculative basis to translate the likelihood of defaults into a score used in daily life is the other component of this practice, given that the predictive likelihood that a model generates does not mean much for many use-cases. This second component of this calculative practice depends highly on productisation, that is, the use of the score with a purposeful, commercial, real-life application:

> We connect our score with different digital merchants, and these digital merchants will run our score and decide the risk

> level that they can accept. In this, for example, they can accept users of a credit score of 600; the people who have a credit score of 600 and above can have that digital service.
> — Product manager from Company 4.

The established acceptable standards for the score depend on the merchants who are using it. The act of acknowledging the acceptance of different levels of the score, in a way, sets up a standard, though this system of the standard is relatively arbitrary as it is chosen by merchants differently. In this case, merchants' risk appetites were integrated into the underlining calculative logic based on business application and use-cases among users and commercial partners.

Although the standards for these different credit scores fluctuated, a norm to stay reliable and repay debts was *de facto* set up through the product rules of creating constraints and punishments if a person failed to repay.

> When a consumer has a discredit behaviour, for example, breaching a contract when using a merchant's service, we will ask the merchant for the discredited record, and then we will set up some penalty.
> — Product manager from Company 5.

With ever-expanding product optimisation, consumers had access to more daily services if they had a decent credit score. In using these services, the credit scoring team absorbed more data for better model production. However, despite all of the variations in the credit scoring models that the eight companies put together, the focus and new usability of the credit score enhanced the awareness of creditworthiness as databases of unreliable behaviour were synchronised in real-time and as consumers understood the benefits and constraints constructed around that behaviour.

The power of the technology described in this study is deeply present in consumers' daily lives and guides calculative thinking as they find that subjecting to this ever-expanding use of the credit score can facilitate their life choices and bring convenience. In this case, the calculative practice (the credit scoring model and its application) manifested as product optimisation, i.e., the iterative process of collecting more data, improving models and working with merchants to target models for specific use-cases.

Product optimisation considers psychological effects to retain and attract more consumers to use products that are tied to their credit score. This, however, was not the programme's original aspiration. The findings of this study suggest power effects similar to those found by Miller and Rose (1990, p. 3), who explain that expertise is a key role for generating the assemblage of techniques because expertise is informed of both the technical features of production and capacities of individuals, such as a subject's psychological condition and productivity. On the other hand, for consumers, this engenders issues such as invading consumer privacy and processing consumer information without consent. This creates an effect of shaping consumer behaviour, populating the idea and usefulness of becoming rule-abiding.

### 6.2 Regulatory rejection of the ever-expanding product optimisation

In 2017, the eight companies were waiting to receive the final license results. However, for two years, since the first notice in 2015, they had not received a confirmation. In April 2017, the governors from the PBoC gave a speech and stated that the technologies developed by the companies did not meet the regulatory expectations.

The central bank governor, Cuizhi Wang, explained that each of these companies relied on their resource advantages and formed a closed business cycle for their business operation. In this way, information sharing was divided, as each company protected its data source for competitive advantages, and the creditworthiness standard based on this fragmented information was not objective and comprehensive.

Second, these eight companies looked for different data and based their credit scoring practice on the limited data that they accumulated. They did not comply with rules and ask for consumer consent for the credit registry and the core concept of credit scoring. They used a vast amount of consumer data to predict creditworthiness, which was incorrect, as it created injustice. Moreover, the central bank was worried that each of these eight companies all belonged to a large commercial enterprise or business group, which hindered the independence and objectivity of credit scoring. Wang explained that credit scoring should mainly use data from the financial credit domain, and its use-cases should be constrained to the financial domain.

This opinion from the PBoC indicated a changed programmatic demand and created a new environment for the industry in January 2018 (Xinhua, 2018). PBoC issued only one license to a newly founded company called Baihang; the eight pilot companies each hold 8% of its shares, and the National Internet Finance Association of China is the biggest shareholder, with 36%. As a consequence, the eight companies stopped providing their credit scores to other lenders and now only use them for internal purposes. They also stopped marketing their products as credit scores, but rather an organisational productisation scores, such as Company 5 kept their own scores for the purpose of lending and other rental service. In 2019, the government accused the CEO of Company 3 of selling consumer data to credit collection agencies.

The newly established Baihang is now building a database of the internet lending credit history with the goal of eventually capturing all of the markets. The data includes elements that the eight companies find useful in their experience of building products with their datasets. It builds credit models using only traditional financial credit data while integrating certain data points that were found useful by the eight companies, e.g., phone numbers or delays in reporting delinquencies to a credit agency, and excluding some data elements related to user privacy, such as spouse name or browsing history.

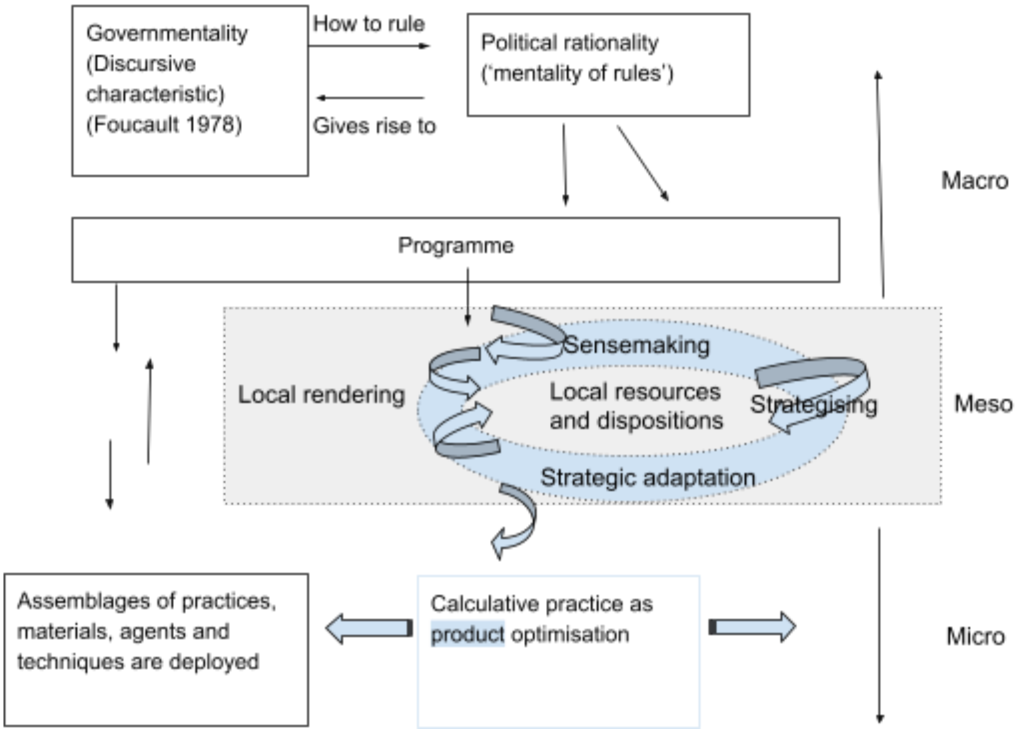
## 7. Discussion

In this paper, we described how organisations, through local rendering, adapted the state programme to align with their strategic visions. In other words, rather than adapting the organisation to meet the needs of the government, the organisations adapted the government programme to meet their needs. I developed the concept of local rendering to identify the missing meso-level mechanisms that impact the development of the calculative technology and to understand the linkage between the state programme and the calculative technology in the governmentality literature (Diagram 1).

Historical research in the Foucauldian vein has mainly been conducted through archival studies and historical accounts. Given this methodological constraint, the interrelationship and interaction between political rationality, programme and technology were shown mutually constitutive. Based on ethnographic data and interviews, this research adds on to demonstrate how the link between the programme and the calculative technology is constructed. In explaining the meso-level alteration of the programme, this research highlights the meso-level reasons that caused the technology to fail to realise the programmatic aspiration.

Sensemaking, strategising and strategic adaptation are shown in the data as important organisational processes both prior to and throughout the phrase of technological development. In particular, organisations conducted sensemaking of the programme by trying to anticipate what the state aspired to in relation to why they were selected, rendering their organisational, local resources. With continual strategising and strategic adaptation, these organisations further used that programmatic discourse to support what they strategically aimed to achieve and were able to build, rendering their organisational dispositions and further enhancing their organisational capability, and tuning their technology to perform better.

**Diagram 1: Contribution to Governmentality framework**




Overall, the development of the technology and the understanding of creditworthiness were constructed around the organisations' local resources and dispositions, emphasising an entrepreneurial rendering process of localisation. By analysing the detailed account of how organisational actors perceive and construct the link between the calculative technology and programme, I addressed the role that localisation plays in the overall process.

Zuboff (2019, p. 233) uses the term 'rendition' to describe the concrete operational practices through which the acquisition of human experience as data is accomplished for datafication, which covers the intermediary practices and processes from data manufacturing to sales. Rendition refers to the interpretation of consumer behaviour. A similar empirical effect of data analytics is also observed here, but this case demonstrates a creation process of organisational technology. I use 'local rendering' to refer to the meso-level activity of organisational sensemaking, strategising and strategic adaptation to adapt the programme and redirect the direction of Big Data calculative technology development, which, in turn, generates invasive effects of the calculative practice as product optimisation.

For example, while turning the social aspects of information (such as social network, consumption or bike rental data) into forms of economic information (information for credit scoring), the calculative technology produces a calculative area by rendering the social into the calculable and governable (Latour, 1987; Mennicken and Miller, 2012) to benefit organisational needs. It continues to shape consumer behaviour: not just spending habits but wider behavioural patterns, such as returning a bike properly on time or being mindful of using the same credit score to obtain various services to boost the score. However, it becomes difficult to explain the relationship between the score and creditworthiness, and the technology creates injustice, as it constantly judges people by their various behaviours, which may be trivial. Moreover, the organisations overly process and collect consumer data, which turns the calculative technology into an invasive technology that expands and suits commercial interests.

The state rationality and aspiration of ‘building a trustworthy society’ address the societal problems of trust-breaching and economic misconduct. In contrast, this macro-level rationality (Kurunmäki and Miller, 2011) remains broad and relies on various technological installations (Rose, 1999a) of micro-level details. However, this study focuses on organisational innovation as an important middle-ground of observing the interplay of different actors in the development of calculative technology. Such a perspective is particularly useful, as it provides a theoretical grounding to evaluate the unintended consequences the emerge in-between high-level programmes and low-level operations, seeing actors as an entrepreneur imbued with strategic thinking.

Moreover, this research speaks back to governmentality studies on China, where a form of neoliberalism has been documented: ‘one that is both authoritarian in a familiar political and technocratic sense' (Sigley, 2009, p.506) derived after the Chinese economic and market reforms starting in the 1980s. As socio-economic governance in China made its way from a centralized planned economy towards increasingly governing subjects through their own autonomy, rationalities of government emphasise the need for citizens to be self-responsible, autonomous and entrepreneurial individuals (Bray, 2006; Hoffman, 2006; Jeffreys, 2006; Sigley, 2006; Jeffreys and Sigley, 2009, Zhang, 2018; Palmer and Winiger, 2019) with mechanisms such as 'danwei and hukou' deployed to reconfigure ideal subjects via 'categorization and differentiation' (Bray, 2006; Zhang, 2018).

The concept 'local rendering' contributes to understanding the particular formation of technology under such a governmentality regime, where the role of the central government is still strong (Zhang, 2018) and recently turned to the configuration of algorithms for 'categorization and differentiation' purposes. This research illustrates that different actors work with different local resources and different local dispositions which, in turn, morph the programme outcomes for commercial ends. At a distance, the programme still promotes the main rationality of a trustworthy society that the state set out to propagate. Moreover, as Chinese governance is based on principles and centred around setting in motion different actors to implement these principles (Goldstein, 2005; Jones and Zeng, 2019), local rendering helps us understand calculative practices in a new light and encourages policy makers to include on their policy radars localisation processes and the messiness of implementation, issues that are often neglected by governmental programmers.

## 8. Conclusion

'The mountains are high, and the emperor is far away' is a Chinese proverb used to describe the idea that the central authorities are far removed from the local affairs and may not be able to influence them. This paper is concerned with the same effect of the state programme being at a distance, and the organisations altering and adapting the programme at their local level to suit their needs. By using organisational accounts to illustrate how the linkage between the programme and the technology is developed, this paper argues that the intricate linkages between calculative technologies and the programme are manufactured through the meso-level actors. It brings attention to the governmentality literature that has been ‘macro’ and ‘micro’ centred, that there is another organisational ‘meso’ level that is important for analysis.

I observe that when organisations received test licences to carry out credit reporting, they needed to make the programme operable. They conducted sensemaking, strategising and strategic adaptation, which emphasised their local initiative of rendering their resources and disposition. I develop a concept of local rendering to pay attention to such a process. During the process, the political programme was used by the organisations to conduct credit reporting as product optimisation, creating an invasive impact on consumers’ lives.

This study informs regulators who are building a state project to pay attention to the unintended consequences brought about by transmitting and delivering the political rationales. Moreover, important attention needs to be put in the realisation process of different organisations and entities, where the differences in local resources and organisational dispositions may create dispersive results in the calculative practice. In the meso-level rendering, localisation is found to be an important factor in realising the calculative practice at the enterprise level. This offers insights for regulators and those seeking to contribute to policy around calculative technology in the use of algorithms and Big Data while mobilising institutions in a state project.

Finally, the focus within this paper was confined to the construction of the state programme in the Chinese context, as illustrated through organisations’ effort on such a technology creation. A fruitful area of extension is to research how the concept of local rendering applies to other situations, such as other cultural settings or environments where the government uses different methods and instruments to mobilise various institutions and fulfil its political aspirations.

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# IV. Credit Modelling in an Algorithmic Cage: How a Calculative Culture Affects Access to Credit

**Abstract**

There is a growing belief that online credit platforms can transcend geographical boundaries and increase financial inclusion. This belief, however, overlooks the potential effect of algorithmic injustice and injustices that can constitute exclusion. This paper examines the production of credit scoring models and the analytical algorithms used to quantify consumer creditworthiness and determine consumers' access to credit. Based on 695 hours of ethnographic fieldwork in a team of credit risk modellers from a large internet company in China in 2018, this study reveals the calculative culture that underpins such practices and argues that the development of algorithmic credit scoring places itself into an 'algorithmic cage' of its own making. First, modellers rely on statistical and machine learning algorithms to select variables of high statistical significance. Their pursuit of high results on statistical measures of model performance makes data quantity and quality critical in determining the judging variables. Modelling injustice is not eliminated. Second, consumers whom the model cannot evaluate due to insufficient data are filtered out from access to credit. Third, model developers run real-life experiments to gain consumer data to further target specific consumers, which shapes needs for credit. This paper contributes to an understanding of a reductive calculative culture that turns the evaluation of creditworthiness into a simple judgment of statistical significance and show how biased data emerges and shapes future access to credit. This research informs future quality control of algorithm production with regard to algorithm injustice.

**Keywords:** Algorithmic injustice, Quantitative Measure, Credit Scoring, Calculative Culture, Financial Access

## 1. Introduction

Algorithmic decision-making and decision support systems are increasingly being deployed to produce quantitative measures in all realms of life (Mennicken and Espeland, 2019). The application of statistics, computer programming, and expanded data storage have made the quantification and calculation of consumers' personal digital traits a necessary input for algorithmic decision-making. This growing algorithmic method of calculation and quantification with Big Data comprises a new format and gives greater power to calculation (Zuboff, 2019). An 'algorithmic economy' (Bamford and MacKenzie, 2018) is coming into being.

Parallel to these technological advances, concerns have arisen about the non-transparent algorithms constituting a 'black box society' (Pasquale, 2015). Because organisations use proprietary algorithms, we still do not know enough about how these algorithms are created. The production of these algorithmic calculative technologies needs to be considered, due to the issue of algorithmic unfairness (Kearns and Roth, 2019; Marcus and Davis, 2019), i.e., favouring or discriminating against a certain group of people, and structural injustice (Noble, 2018; Benjamin, 2019; O'Neil, 2016), i.e., replicating disempowerment of members of particular social groups. Without examining how the production is being organised and how these algorithms are configured and used, it is difficult to ensure the quality of these algorithms, the impact of which is so far-reaching.

Moreover, financial services and infrastructure are constantly moving to the online space (Pardo-Guerra, 2019). Digital inclusion has become critical in helping 'reach underserved, vulnerable and remote populations…who don't have access to bank accounts and ensuring business continuity' (The World Bank, 2019). This is even more true in the time of COVID-19 and widespread lockdowns. Credit services, for example, have moved online. The promise to build creditworthiness assessments using personal data (Aitken, 2015;

Guerin and Kumar, 2017; Servet, 2015) that do not require credit histories or collateral has been seen as a major measure to expand financial inclusion (IMF, 2020). However, while the discussion above on financial inclusion focuses on access to the infrastructure and the discriminating interest rates (Langevin, 2019), it does not consider the potential algorithmic injustice built into the credit models.

The production of algorithms depends on modellers' specific practice using statistical, machine learning models and setting rules for calculation. Svetlova (2018) and Hansen (2020) analysed the different attitudes towards decision-making in model usage with machine learning features in finance and risk management. Hansen (2020) proposed using 'pragmatic idealism' to contrast the two sets of attitudes towards model use in different stages. The idealistic usage of model results seems dangerous, given that the question of whether the specific configuration of algorithmic production results in or alleviates algorithmic injustice has not been resolved.

In understanding the use of financial models (Svetlova, 2018; Hansen, 2020), more attention has been paid to the calculative culture in shaping the use, preference, configuration, and limitations of calculative technologies in organisations (Bhimani, 2003; Power, 2003, 2007; Mikes, 2009). Calculative culture can be understood as the 'specific practices of integrating models into financial decision-making and combining them with emotions, views and stories of their users' (Svetlova, 2018, p. 4). However, with new algorithmic calculative techniques and practices emerging, a calculative culture underpinning the 'algorithmic economy' (Bamford and MacKenzie, 2018) needs to be examined.

Motivated by the serious gap of algorithmic production and the increasingly widespread use of algorithmic credit scoring, this paper examines the production of consumer credit scoring algorithms deployed in the credit provision technology in China. This research's empirical data is based on ethnographic fieldwork in a credit modelling team of a large internet company in China. The company holds one of the largest proprietary consumer datasets in the country. Their basic scorecard models were initially set out to issue a quantitative credit score covering the whole population of China. It was one of eight companies selected by the Peoples Bank of China (PBoC) for a test licence to conduct credit reporting. Subsequently, the observed team mainly served as risk management for the company's online micro-lending and other online lending products.

This study investigates the process of developing the credit models and draw attention to the concept and ideation behind this calculative practice of configuring a credit scoring technology that integrates Big Data modelling and machine learning features. It focuses on the underlying calculative culture and, importantly, on how modelling injustice emerges. It aims to capture the calculative culture that permeates the production of credit models, i.e., constructing an algorithmic measure in the context of an ever-increasing 'algorithmic economy' (Bamford and MacKenzie, 2018) and 'surveillance capitalism' (Zuboff, 2019). It also examines the model developers' decisions in the modelling process that can impact financial exclusion.

The rest of the paper is structured as follows. In section two, I introduce related literature on calculative culture and the performativity of financial models, which I use to understand and analyse our case. Next, in section three, I discuss the qualitative methods that I use to gather, analyse, and theorise our data before presenting our empirical findings of modelling in an 'algorithmic cage' in section four. I then consider how credit technology shapes financial exclusion in section five. I go on to discuss our theoretical contribution and its implications in the concluding section six, followed by conclusions in section seven.

## 2. Literature review

### 2.1 Calculative culture and financial models

The increasing automation of calculative algorithms does not signify the removal of human judgements. Rather, the development of algorithmic systems involves humans making attentive choices. In this case, modellers play an important role in configuring models that are later deployed as algorithms. In seeing the enactment of technology as a specific configuration and arrangement of persons, materials, and tasks (Barley, 1990), I observe the configuration of models and the use of advanced machine learning techniques, which are, nevertheless, socio-material productions (Orlikowski and Scott, 2015). With regard to the specific decisions and beliefs of modellers in the configuration process, the 'notion of practical action', where cultural elements act as sources for action (Stark, 2009, p. 165), is deemed critical in understanding calculative algorithms in this context.

Calculative cultures help understand the recent turn of the prevalent use of quantitative measures (Power, 1997; Strathern, 2000; Hoffer, 2000; Humphrey and Owen, 2000; Shore and Wright, 2000). By underpinning technological choices, the concept of calculative culture has helped to fundamentally explain the successful adoption of a specific calculative feature in the information system (Bhimani, 2003). For instance, Mikes (2009, p. 34) explains that a calculative culture favouring management by numbers causes the integration of analytics' function in risk management, which makes risks quantifiable and subject to restraint and control. In view of this, calculative cultures can help respond to the adoption and integration of technological functions in calculative practice.

Calculative culture can be understood as the 'specific practices of integrating models into financial decision-making and combining them with emotions, views and stories of their users' (Svetlova, 2018, p. 4). This definition describes both the coherence and distinctiveness of model use in different contexts with regard to different organisational arrangements, procedures, and ontologies. For instance, when Power (1997, p. 71) looks back at the adoption and consolidation of statistical sampling approaches in the late 1890s and risk modelling in the mid-1980s in the auditing process, he comments that the use of these techniques in auditing is ‘cultural as well as economic’ (Power, 1997, p. 73). He appeals to the understanding of using these techniques as a part of the ‘rituals of verification’ of auditing. These techniques were integrated into the evolving framework of auditing practices, where auditing knowledge adhered to the legitimate body of statistical information and technical values. Likewise, practitioners’ judgements and intuitions were not replaced by these techniques; rather, they remained essential in performing the best practices.

When studying models, we must come to understand that the use of models is embedded in an organisational process (MacKenzie and Spears, 2014a, 2014b) that facilitates decision-making for the firms, organisations, and individuals involved. The use of financial models is important for making sense of ‘financial objects’ (i.e., trades, products, and marketplaces) (Muniesa et al., 2011, p. 1189) because they offer analysis and a description of environments that have to cope with increasing complexities (MacKenzie and Millo, 2003). Meanwhile, MacKenzie and Spears (2014a) use the term ‘evaluative culture’ to pinpoint that traders’ use of financial models across various organisations can affect each other once they find the models useful.

Moreover, the specific use of models can vary from organisation to organisation (Lépinay, 2011) with regards to internal communication or the inventive use of models as ‘creative resources’ rather than fixed rules (Svetlova, 2012). For example, in the study of using models in the trading of derivatives, Beunza and Stark (2012) find that traders are aware that the models they use could be wrong. As such, traders use the models while retaining ‘cognitive distance’ and thereby exercising ‘reflexive modelling’. This means that traders consider the model results to inform them about others' beliefs on pricing, allowing them to compare those beliefs to their own (Beunza and Stark, 2012, p. 411). In this way, traders use these models with a pragmatic approach. In addition, MacKenzie and Spears (2014a) find that Gaussian copula models in investment banking were mainly used for governance and communication purposes, where 'creative, resourceful and well-informed' human actors could exploit the role of the models, subsequently contributing to the global financial crisis.

Particularly, Hansen (2020) summarises two distinctive calculative cultures: idealistic versus pragmatic (Power, 2005; Mikes, 2009, 2011), underpinning the different attitudes of model use. He explains that idealists, whom MacKenzie and Spear (2014a) refer to as 'model dopes', believe in the model results and uncritically use the model output. On the other hand, calculative pragmatists do not trust models to produce an accurate representation of reality (Svetlova and Dirksen, 2014; Wansleben, 2014, p. 608; Svetlova, 2018, pp. 69–70). These distinct cultures demonstrate the different ontologies behind the use of models, which affect the integration of model results in decision-making (Mikes, 2011, p. 240).

When it comes to studying machine-learning models used in finance, Hansen (2020) advocates for 'pragmatic idealism' – the third type of calculative culture, which incorporates both pragmatic and idealistic attitudes toward models. The term 'pragmatic idealism' suggests that pragmatic considerations take place in the process of devising complex adaptive models, while model users are idealists. Such a mixed attitude indicates a distanced and even contradictory practice between the implementation of machine-learning models and the use of model results. Meanwhile, it highlights that models have become increasingly important to decision-making, given that model users are more idealistic about the model results.

Being aware of the pragmatic attitude in implementation is not enough to explain the specific array of technical arrangements and the specific complication of human and material actors in the production of the models.

Moreover, when investigating the production of quantitative indicators and access to medicine ranking, Mehrpouya and Samiolo (2016) explain that 'epistemic work' plays an important role. They show that experts' 'trained vision' can have different ways of 'seeing' in terms of comparison and benchmarking and is shaped by the goals of stakeholder consensus. Therefore, a more in-depth analysis of the modelling process is needed to account for how the variables selected in the model as objects of knowledge are 'learnt' and how the consumer quality that links to credit default is 'seen'. This will allow for a deeper understanding of the production of algorithmic measures of consumers' creditworthiness.

### 2.2 Model performativity and financial exclusion

Understanding the production side of the financial models is also crucial for grasping the elements that facilitate how finance operates (Latour, 1987; Callon, 1998). Literature that contributes to the social study of finance has highlighted the role of organisational and technological arrangements in constructing financial markets, with increasing attention being paid to the 'performativity' of financial models (Svetlova, 2012). How the model developers configure and use the credit score models determines who is more creditworthy and who is not. Credit score models, therefore, have a performative characteristic in affecting financial inclusion.

'Performativity' was initially a concept coined by J. L. Austin in his understanding of the influence of speech. Austin (1962) distinguishes 'constative language' from 'performative language'. Unlike constative language, performative language does not offer a statement of truth; it is not 'truth-evaluable'. Performative language refers to how articulated speeches are a part of doing (or part of) an action itself. This means that performative speech gives rise to action and brings about a reality, rather than just a mere description of reality. The understanding of this mode of speech was later applied to the understanding of financial models.

‘Performativity’ reflects the important function of financial models: they do not only describe or provide the ‘truth’ but also shape and format financial order and structure through making economics and finance operable as infrastructures (Callon et al., 2007). MacKenzie (2007, p. 6) explains that the specific knowledge forms and models can engender and create a specific economic order depending on their specific configuration of this economic knowledge and tools. The outcome of collective beliefs or related institutional and technological settings can prosper in certain market practices.

For instance, MacKenzie and Millo (2003) studied derivatives and the Black-Scholes formula model, finding that traders at the Chicago Board Options Exchange used the Black-Scholes model in reverse to estimate stock volatility. The rapid use of this modelling approach resulted in direct effects on market prices, as traders learn by first betting according to the volatility skew, then later betting against the skew to make returns due to an over-learned options market. Their study provides an example of the ‘performativity’ thesis. They elucidate that the financial model’s success is not due to a self-fulfilling prophecy (Merton, 1949), but rather due to the specific configuration of technological practices and the embeddedness of market actors.

The implementation of digital technologies for ‘financial inclusion’ is believed to be particularly eminent (Bernards and Campbell-Verduyn, 2019). Technological development is radically changing the way that finance works and reconfiguring the financial order (Dula and Lee, 2018). Attention has been paid to the newly included unbanked population in terms of financial infrastructure (Henry et al., 2017) and Big Data accumulation for credit scoring (Aitken, 2015). Moreover, Langevin (2019) considers the limits of Fintech companies in promoting financial inclusion. She draws on two case studies of micro-lending platforms and considers the special agenda and expertise of these platforms for profitability. These attempts induce higher pressure for borrowers to repay growing debts, which makes inclusion dysfunctional.

Overall, credit scoring has entered the centre stage in the discussion of structural stratification. Fourcade and Healy (2016) analytically explain that the prevalent use of market analytics backed by large volumes of quantitative data is constantly evaluating consumers, which creates stratifying economic classification effects that shape life opportunities for individuals (Fourcade and Healy, 2013). It also forms patterns of cumulative advantages and disadvantages in a structural manner, serving as a social leveller (Grandy, 2009).

Kiviat (2019) evaluates the moral limits of using credit scores in determining car insurance prices. She distinguishes predictive usefulness from moral justification. However, she focuses on how policymakers' regulations and worldviews induce fairness. She questions the limit of algorithmic predictions in delivering that fairness. Considering consumers' interests, her research did not explore the construction of analytical models in terms of how they bring structural stratification into being. This paper aims to fill this gap by acquiring the specific configurations of credit models and examining the models' performative effects. It focuses on algorithmic injustice and the practices behind credit technology, which can shape the future of credit needs, demands and choices.

## 3. Methodology

### 3.1 Data collection

**Participation observation.** My ethnographic work involves onsite participation and the observation of modelling work for credit risk in a Credit Scoring Center (CSC) from a larger internet company in China for 695 hours from May to August in 2018, as well as recurrent formal and informal interviews with model developers, modelling supervisors, the credit bureau director, and their clients. This research gathered 469 single-spaced pages (11-point font, standard margins) of fieldnotes and 301 pages of 15 two-hour meeting transcripts. I kept hand-written and typed fieldnotes closely documenting the model developer’s daily flow of modelling work before, during, and after each step, the events they encountered, and their daily discussion and interaction at work. I further participated in modelling with one colleague, noting the detailed steps of a model configuration. I was immersed in the site for long hours, interacting with model developers at work and off work. The data also included semi-structured interviews carried out after the ethnographic observation, encompassing 24 hours of recorded interview material with modelling supervisors, noting model developers’ perception of technology in use and cultural elements of modelling practice (Seaver, 2017).

**Ethnographic setting.** The CSC was issued a pilot license in January 2015 by the Chinese state to conduct credit reporting business for constructing the social credit system. The CSC is registered as an independent entity, but it operates as a group in the branch of the internet company’s Financial Innovation Branch (FIB), including its payment platform. This internet company’s application platform offers messaging, social media, payment, and financial service functionality to its users. The FIB manages the company’s payment platform, facilitating one billion daily payment transactions. Moreover, FIB also provides various financial services, including lending and wealth management. Thereby, FIB can access users’ accumulated digital payment data, investment data, lending data, and some social network data (reflected in the transaction).

As a central bank selected company and a subgroup under FIB, the CSC was responsible for operating the credit-scoring business, and its modelling team was responsible for building basic scorecard models to rate the general population of the whole country (to issue a credit score of creditworthiness) and also conduct risk management for their own lending service. By January 2018, their credit scores had a daily enquiry of eight million, mostly by online lending vendors. However, from March 2018, CSC experienced a major shift for their rating business and shifted their focus to modelling for their lending business and improving their basic scorecard models. This is because the central bank restructured the project of building the social credit system, and they cannot commercialise their credit scoring result to other lending institutes than their working partners.

During the observation period, the modelling team improved the basic scorecard models using a defaulted dataset from online lenders, banks, and their own lending platform and characteristic data from central bank credit history, their proprietary data, and telecommunication data. Also, CSC responds to the lending operational needs for their lending business, including building credit models and strategies to evaluate credit applicants and building response models to target users who are likely to apply for a loan. They also participated in their assets' back security project as a risk control department.

### 3.2 Data analysis

Driven by the research motivation (Benford and Snow, 2000), data analysis begins with interrogating the constituent elements, actors, actions, and interactions between different elements (Langley, 2009, p. 409) in the modelling process and the model impacts. The author then separated the elements of the data into two sections: one is the modellers' thinking and modelling process; the other is the modelling impact on credit access. Afterwards, I paid special attention to the thinking and construction of credit models in parallel to the model result in shaping access to credit, zooming in to understand the micro-process of modelling and zooming out to see the macro-consequence of such practice (Nicolini, 2009; Zilber, 2020). This process was achieved by iteratively reading fieldnotes and interview transcripts, taking into account the surprises and contrast (Abbott, 2004) between the literature of calculative practice of modelling and model performativity, to avoid failing to capture the novelty in the phenomena (Meyer, Gaba and Colwell, 2005). I developed exploratory memos and data descriptions with my supervisors (Corbin and Strauss, 2015; Emerson et al., 2011).

After an iterative process (Yin, 2011; Miles et al., 2014) of the analytical work above and engaging with the data, I came to understand that there is an underlying calculative logic to this algorithmic modelling, shaped by the human ideation, belief, and practice and the given roles of the technical devices and material element as data points. Because of this, I narrowed my review down to the literature calculative cultures and made comparisons from there. Afterwards, the concept of algorithmic cage surfaced in the analysis, for it featured prominently in the way modellers believe in their methods and trust the statistical software to do the job of prediction on Big Data. However, it was initially unclear what constitutes this algorithmic cage. I then keep working back and forth between different elements in the modelling process and other emerging constructs in our data to explore this hunch (Locke et al., 2008). I further deepened my understanding of the algorithmic cage by creating graphic demonstrations to reduce data and capturing critical elements in constructing the algorithmic cage.

To understand performativity in relation to financial inclusion, I focused on scrutinising the relationship between modelling dynamics and model outcomes to engage in a ‘relational process’ to generate codes (Locke et al., 2020) to answer the research question. Holding onto this relational process allowed me to see the interconnection between decisions in the modelling practice and its impact on credit access, where I linked the elements of model limitation and the proactiveness of shaping credit choices to the outcomes of credit analytics.

## 4. Findings: Credit modelling within an ‘algorithmic cage’

Paying attention to how credit models are constructed, the findings explore the interplay between human actors and technology in forming the credit analytics. This section examines the modelling process and model developers' conception and ideation behind their predictive analytics. It discloses a calculative logic of pursuing high statistical model performance throughout the entire process of modelling, which ultimately results in credit modelling within an 'algorithmic cage'.

From the outset, model developers believe in their statistical algorithms and trust the promise of Big Data. They pursue the high statistical performance of their model. In seeing what the statistical software selects as highly predictive variables, model developers learn about the characteristics of possible defaults. With the aspiration to generate higher predictive power of the model on the development samples and testing samples, modelling work faces statistical material constraints. The three sections below explain the three elements that bring the algorithmic cage into being.

### 4.1 Setting intentions for models and material constraints

Modellers decide on the model objectives and use models to answer operational questions. Thus, the model objectives must be well defined, have a robust statistical form, and include a singular time period. The definition of the model objectives permeates the coherence of what the model can predict. As the credit bureau director reminds the model developer about the importance of setting the right objectives:

> Our model sets out to examine the model objective that we set. So, we have to carefully quantify the statistical conditions that we set for our model. For example, if we define our risk event as default in six months, we are unlikely to capture the predictive characteristic, leading to people who default in twelve months.
> – Credit bureau director

The credit bureau director emphasises that setting the model objective is the first step in credit modelling. For them, the model is used to predict which accounts will default and which will not. To do so, model developers need to operationalise the concepts into something quantifiable. Decisions have to be made about the following questions: How long does the account need to be past due to be considered in default? For how long should the modellers observe the repayment of the loan? Answering these questions will help to define the model's independent variables.

In turn, the translation from operational questions to the independent variables reduces the complexity and variety of risky events. A clear definition of a risky event in terms of a timeframe of observation and default as measured by the length of time past due is essential. This implies a transformation from operational questions into quantifiable numbers. For example, a model developer may define a performance window as 12 months and default as 30 days past due. This choice simplifies the data. It considers borrowers who default in month 13 as 'good' and borrowers 30 days past due as equally bad as those who are 60 days past due.

Definitions of 'risky events' and 'default' determine the observation period (performance window). In this case, the data prepared for modelling must be consistent for the same number of months that align with the model objectives, e.g., quantifying risk events in time and value. The definition of the time and value of the independent variable also condition what data is needed to prepare for the modelling procedures. In this case, the data prepared for modelling must be consistent with the number of months in the observation period. A difference in the observation period can result in data showing different characteristics correlated to the risky event. As a result, the change in the observation period leads to different correlated variables.

However, with dedicated model objectives, the model cannot capture risk characteristics for other diverse, alternative risky events of different lengths of time. For example, if a model's observation window[3] is 6 months, its

[3] The period over which the data is observed.

selected characteristics cannot be used to predict people who will default in 9 months. However, different lending products have different maturity windows. [4] The typical duration of credit card loans is shorter than that of a typical car loan; thus, a car loan default may take a longer time to observe. Similarly, a model with the characteristics to predict loans that will deteriorate in 6 months may not predict loans that will deteriorate in 12 months or longer.

Furthermore, model developers explain that the construction of a credit model needs data from loan performance (failed versus paid off) in previous lending cycles, consumer characteristics, behaviour, and repayment to understand the dependent factors for the models' purpose. This necessitates data from various sources in different storage formats that can be summoned and matched.

It is imperative that the data relating to one consumer, though from different sources, is consistently from the same time point. Problems frequently arise in matching datasets for the same consumer because of missing values or inconsistent data points. The material property of Big Data poses challenges for modelling work to meet its statistical requirements.

> The data that we use contains a lot of transaction records (or repayment records), and as such, the data cannot be directly entered into the model. In most cases, the data given to the model should be only one record per customer. Therefore, it is necessary to compress many records of each customer into one.
> – Model developer A

The data quality is heterogeneous, which indicates that data from various datasets is messy before it is compiled into a modelling resource. Model developers need to derive variables from pieces of information about users' attributes, digital service history, and financial product history to fit the data

[4] The period that the debt has shown maturity.

into the model. If the data contain many transaction records, model developers will need to compile all of them to understand whether one account has defaulted yet and thus denote a borrower's financial characteristics.

Only one record per consumer is desirable because one person represents one observation unit. In most cases, data on user characteristics, performance and activity come as one piece of information. This implies that the information has to be reconfigured into a proper storage format/structure so that the statistical software can be used as an input for query and analysis purposes. The material property of Big Data requires modelling work to extract, transform and load (ETL) data to produce intermediate data that can be fed into the statistical software.

In defining model objectives, model developers define the concept of 'good' and 'bad' accounts in numerical formats such as how many 'days past due' the loan repayment is. The model intention was simplified to detect something measurable. Likewise, the notion of creditworthiness, as a rather complex social factor, has been equated to statistical numbers. This section shows a reduction process of defining the model's objective. Moreover, it shows the process of reducing the messiness of the data and organisation of it into structured and organised forms for statistical calculation, where the model developer is constrained in the material properties of data. Data is essential for the whole process of model development.

### 4.2 Machines know better than humans

> Statistical and machine learning algorithms can detect more complicated relationships between two data points – which exceeds human capacity. Its result can help us find more predictive power and enhances our models' predictability.
> – Credit bureau director

> With statistical algorithms, we can quickly detect patterns in large datasets. Machine learning can optimise approximation between inputs and outputs beyond human comprehension.
> – Model developer Z

The current sentiment on what the intelligent machine can achieve is that it has exceeded human capability. This underlying belief, held by both the credit bureau director and model developer Z, exhibits an upgrade of the usability of the machine to judge and predict human credit behaviour. This section examines the ideation behind the way statistical algorithms and machine learning techniques are used in modelling work and how the modellers build credit models.

Correspondingly, behind this ideation, model developers rely on the statistical algorithms and results to construct their models. All of the models at CSC were built following the same algorithmic process. By January 2018, as one of the 8 companies, their model result reached 2 million daily inquiries when it had not even launched its product to individual consumers yet.

Credit modellers believe in the analytical power of statistical algorithms and machine learning techniques. A model developer (shown below) explains how she built a credit model based on the central bank credit history data with the centre's lending product performance, relying on statistical measures.

> In developing models based on the central bank credit history data, we derive 1,800 variables, and through the calculation of information Value (IV) measure, we select 400 variables based on their IV values, and after running it in logistic regression, we select 21 variables based on the coefficient. We also perform a neural network. Z (model developer Z) runs 23 variables in the neural network. The model predictability shows a 5% increase.

– Model developer R

> We derive a lot of variables based on the data we have. Then we run statistical calculations on these variables. We select variables based on the statistical presentation. So, the statistical results play an important role in our variable selection process.
> – Model developer C

A characteristic analysis is used in the variable selection process. The model developers use the IV to judge how good statistically a derived variable can distinguish and define ‘good’ and ‘bad’ accounts. It helps to rank variables on the basis of their importance, and it screens out weak characteristics. Modellers will use the variables without further questioning after they check the correlation between the selected variables. Modeller T noted that it is also important to determine those characteristics of high IV not correlated with each other to include them in IV calculations during the next round of variable selection.

Herein, statistical reasoning becomes the justification for variable selection. Model developers use IV methods followed by correlation analysis to decide what is more statistically predictive. In this, the variables of high IV and statistical contributions are believed to be good indicators of predictability. The modellers’ practice of relying on the statistical selection of the predictive variables indicates a trust in technological results. In effect, statistical calculation provides statistical reasoning to replace human judgement in evaluating consumers’ creditworthiness.

Following up model developer R’s statement, model developer Z introduces the new neural network that she develops in a flow chart (Chart 1):

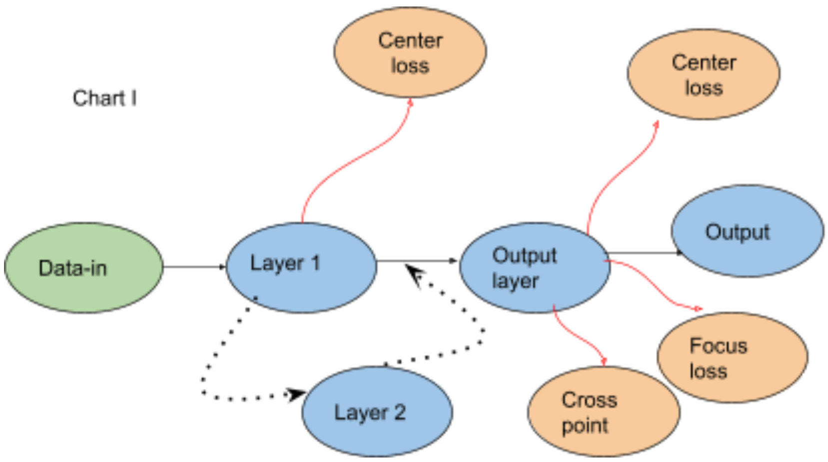


Chart 1: Neural Network illustration (Source: Internal organisation document)

> I tried using some new nodes and adopted two approaches to metric-learning. The dotted line in the chart is a new neural network structure. The one I adopted is without the dotted line. The red line marks the position of centre loss and focus loss.[5] In this case, KS (Kolmogorov-Smirnov score) raises 10%.

The calculation process and the eventual result of neural networks are difficult or rather impossible for humans to understand intuitively (Burrell, 2016, p.5). For example, in the above neural structure, layers 1 and 2 are hidden. It is within these hidden layers that the computation of the weights and biases of the data occur, based on the training of the neural network. It is not obvious or tractable how these calculations create the outputs from the inputs. Machine learning keeps many of the working parts concealed from the modellers.

It is known that non-transparent characteristics of neural networks make the decision generated by the model more difficult to trace and explain (Hansen,

[5] Centre loss reduces the distance of each data point to its class centre; Focal Loss reduces the weight the values it predicted correctly carry.

2020b; Michalski et al., 2013). Moreover, in this case, machine learning does not equal human learning, which is an accumulation of knowledge and understanding of the subject matter. In the absence of human learning, modellers are not able to develop new insights into credit behaviours. This means that the expertise and insight are constrained in running the neural networks rather than understanding the underlying question of creditworthiness.

The developers act as if they understand what underpins creditworthiness – in but, in fact, they do not and cannot understand. They rely on a Kolmogorov-Smirnov test (KS) to tell them whether the neural network has helped them improve the model's predictability. A KS test is a statistical measure that can produce a chart for measuring the degree of separation between positive and negative distributions. Thereby, it can tell whether the current model is good at separating good and bad lending accounts.

Moreover, model developers also expressed their entrusted endless possibilities with Big Data.

> In statistics, we believe that if the scope of data is big enough, we can derive as many variables as possible to represent the world.
> – Model developer B

> In statistics, we think that if data is representatively big enough, we can make sufficient inferences.
> – Model developer A

By using statistical algorithms and advanced machine learning techniques, modellers can focus on inputting more data and placing more trust in the numerical result. This gives rise to another important factor in the modelling process: data. The above remarks by developers A and B were made in an ethnographic discussion that followed a meeting held to brainstorm ways to increase their model's predictability.

> The purpose of this meeting was to invite you guys to think about how to improve our model predictability. I would like to hear some suggestions to see how we should strategise from here.
> – Bureau director/meeting host, to the team

> I think we can think more about how to get more data by working with other groups in our tech company.
> – Model developer C


> I think we can think more about how to get more data by working with other groups in our tech company.
> – Model developer C


> We can also still think about working with other data vendors.
> – Modelling supervisor

> Do you mean more data for the Y (credit behaviour data) or X (consumer characteristic data)?
> – Bureau director, to the team

> We mean data for X because this would allow us to find out more predictive characteristics.
> – Model developer C

The modelling team sought to improve model predictability because the current models were less predictive than models built in the previous year. The KS score of the previous model (that was measured based on the development and testing sample) was 50. The current model's KS score is about 35. In this brainstorming session, the model developers proposed ways to access more data, particularly consumer characteristic data. They see getting more consumer characteristic data as having the potential to enhance model predictability. In fact, other methods were raised. When their model stands at a low point of predictability, their standard remedy is to seek more data.

> Based on the type of data, we do data mining, in which we derive vast quantities of variables so that we can see which one has more predictive power.
> – Model developer A

As shown before, Model developers A and B explained why this approach is taken. Model developers welcome the idea of having more data. Furthermore, model A explains that with more data, they can derive more variables from which to select. This gives them the chance to select variables that carry higher statistically predictive power. Through this ideation, they foresee a fuller representation of the world when there is a larger quantity of derived variables. The quotes above demonstrate model developers' attitudes towards Big Data that can account for this situation. Model developers put themselves in a vision cage of how to see the world. They become single-minded in their quest for more data and their pursuit of a path of higher statistical contribution.

In the variable derivation process, model developers mechanically generate more than 1,000 variables based on the transaction (repayment) records corresponding to the transactional sum, average total, and different time points (e.g. recent one month, recent three months). The different transaction dates can identify overdue accounts, accounts with fixed repayment dates, and other details. One derived variable represents one dimension of the information, such as the characteristics associated with the risky event.

> After the brainstorming meeting, the modelling supervisors reached out to external data vendors to source data samples to test whether the data helps with better predictability for the models before buying them. They eventually purchased the data, as it improved their models.
> – Fieldnote excerpt

Furthermore, without actually running tests on the data, the model developers would not be able to discern whether the data helps them improve their model's statistical performance. The statistical measure helps model developers to estimate the usefulness of the data. Based on data availability, many variables can be derived. These derived variables become the choices among which the statistical algorithms are going to decide.

Overall, this section shows the modeller's trust and belief in the possibility of Big Data, statistical and machine learning results. This leads model builders to take a narrow path to the algorithmic cage. Their mechanical way of variable derivative practice and reliance on statistical and machine-learning measures of statistical contribution let statistical reasoning decide who is more creditworthy and who is not. Moreover, model developers are constrained in what they can see by the availability of data and the transformation of data into variables, where its predictors cannot move beyond derived variables and calculated statistical contribution.

### 4.3 Exhaustive pursuit of high 'KS', a statistical measure of model performance

Model developers are in a never-ending attempt to discover characteristics that accurately differentiate the good borrowers from the bad. However, this 'good' means that the model can demonstrate a high value in their statistical measure. The measure used by the team is a high KS score, based on the development sample and the testing sample. An increase in the Kolmogorov-Smirnov test (KS) score means an improvement in the predictability of the model. Model developers ultimately focus on the KS score, and I argue that they lock themselves into a algorithmic cage by doing so.

> If I can find a group of characteristics that can carry high predictive value to include in my credit model, the developed model can be very predictive. The strong predictor we choose here fits our data very well.
> – Model developer L

Model developers believe in the goodness of fit of the data to show a good statistical measure. The strong predictive characteristics are trusted to distinguish ‘good’ accounts from ‘bad’ accounts in the development sample, meaning that a predictive variable has to explain the sample data statistically.

> When the directors went through the model predictive measure, the KS was quite disappointing – lower than last year. He said that in this case, KS did not matter so much. The model developers rebutted that higher managers only care about KS because they know that KS measures the model predictability.
> – Fieldnote excerpt

> When I asked the bureau director why they use the KS score as the ultimate measure, the response was that it is a recognised, standardised measure used by banks and other financial institutions.
> – Fieldnote excerpt

The community of the model developers believes that if an improvement of KS is made, model predictability is increased. However, KS scores can only determine the model’s ability to differentiate the ‘good’ from the ‘bad’ sample points within the boundaries of the testing sample. This includes a reductive nature of seeing the 'good' and 'bad' in the quantification of numbers (e.g. how long does the account need to be past due), and moreover, seeing the validity of the model based on the number (the KS value).

It is evident that it is the managers in the organisation rather than the developers who equate better KS scores with better models overall. As other financial institutions and similar groups inside the company use the KS score, upper managers place expectations for higher KS values on the model developers to compete and contrast.

For instance, in a mid-year organisational report on model results, developers reveal the improvement in model development to the organisational leader. The whole presentation by model developers is carried out in such a way as to report only the basic parameters, such as sample size, sample period and importantly, the KS score of each model developed:

> To show the improvement we made to the model, we can simply see that in the right column of the presentation slide, the KS score of the v5 (version 5) credit scorecard model in both the development sample and the cross-test sample approximates 39%, which is about twice the increase compared to v3.
> – Model developer Y

The prioritisation of a high KS creates a tendency for the model performance to be adjusted to the point that the model works well on the development and testing sample. To do that, modellers want to find more data that will bring a higher KS, as more data can increase the availability of derived variables for the statistical algorithms to choose from (as shown in the last section).

Moreover, the practice and knowledge of modelling are shared within the community of model developers and communicated in the language of statistics. Importantly, the same applies to the validation and trustworthiness of the model. In delivering the result of the modelling work, the validation and substantial proof of the model are expressed in the domain of statistics. The end question for the modellers is not how their models interact with the world, but how predictive the models are in statistical conditions (development and testing samples).

## 5. Credit technology in shaping access to credit

Given data constraints, the models do not work well on certain groups with less data representation or insufficient understanding of the suspicious group. When a model cannot arrive at an assessment of a credit applicant, model developers must decline to offer credit to that applicant. Model developers set up rules/whitelists to filter these consumers. The model's inability to accurately assess creditworthiness results in financial exclusion as one of its effects. Other invasive techniques must be employed to amplify consumer preferences and target those consumers who need credit while filtering out those who do not. This hinders capacity for the practice of making proactive targeting for shaping credit access in addition to credit modelling.

### 5.1 Judging from the imperfect world of data

in addressing how the developed models are used in lending decisions, model developers emphasise the importance that models play in understanding consumers, especially their awareness of the needed extensions of the efficacy of the model. Model efficacy depends on how the model was designed and what it was constructed to evaluate (model objectives). To evaluate more consumers, various models need to be built, as suggested by both model developer T and credit bureau director stated in a weekly meeting:

> Our job is to build models that will work well to evaluate consumers. So, if we can understand more consumers through our models, more credit applicants can be allowed for credit.

> – Model developer T
>
> Let's say, if before we needed to reject 100 credit applicants, we hope with the iteration of our models, we can reject 65 credit applicants – but we really need to build more models considering people of different groups and also different lending scenarios.
> – Credit bureau director

These statements indicate the power of the model in determining who receives credit approval. The lending decision fundamentally relies on whether there is sufficient data available for the model to arrive at a judgment. As an example, model developer T states that if their model can accurately evaluate more consumers, then more consumers are likely to be trusted for credit approval. Conversely, if the model cannot properly recognise or understand a certain group of consumers, their credit applications are likely to be rejected. This indicates that the extension of model development helps to understand and include more consumers for credit access, but it also means that limited model efficacy can result in more exclusions from credit access.

The credit bureau director, quoted above, also expressed the same grand wish of understanding more consumers through their models in a meeting, but he said it was more as a task assigned to the model developers. The credit bureau director states that they need to build more submodels to understand different groups and lending scenarios. Depending on how the model is set up, the development sample is important in deciding whether the model can make an applicable assessment, both for the dependent and independent variables. As a result, he urges the model developers to create different submodels, considering people of different groups and different lending scenarios.

> We need to keep developing models all the time because as regimes change (Time changes – crisis happens, in which more creditors cannot repay their loans; The characteristic of the credit applicants changes in one platform), our models may not be predictive. The default rate of consumer finance has increased lately; the previous models may not be applicable.
> – Model developer A

The developed model needs to be updated to fit changing circumstances and expanding crowds of borrowers – the algorithmic cage and its implication. This is because, in the setting of Big Data credit modelling, model efficacy is limited to the model objective and the characteristics present in the development sample. Whether the model makes accurate predictions depends on the future lending scenario and its similarity to that used in the development sample. This poses a challenge for credit technology to understand and judge people of various groups in various lending scenarios. It must be considered that either the quality of the consumers on different lending platforms or the characteristics of different lending scenarios (e.g., whether the loan is to buy a car at a retailer versus instalment credit for appliances online) is different. It also requires model developers to constantly recalibrate and retrain the model as the environment and the data captured from its change.

Judging people who have less data-trace or less data representation is also beyond the models' ability. Models with selected variables will need to judge applicants' selected characteristics, and this cannot be applied to people with less digital trace. In this empirical case, the models are not used in judging certain groups, as models cannot differentiate whether such an applicant is 'good' or 'bad' at avoiding defaulted circumstances. Model developers only include people for credit service in the beginning.

> There are a lot of customers that we cannot judge based on our data. So at the beginning of the period, we choose to be cautious. We just release our service to the ones with rich data. We use whitelisting to set restrictions on credit applicants. Rules of the whitelist are related to our digital payment behaviour or social behaviour.
> – Model developer T

As model developer T explains, models sometimes fail to recognise a certain group of people with less representation in the data or with fewer data elements. When people have less data-trace (digital payment and social network data in this empirical case), the model cannot make a correct assessment because it makes assessments based on these characteristics. To resolve this situation, model developers must devise strategies such as setting up whitelists to filter the borrowers that they cannot recognise due to the model's limitations. Only people who have digital or payment behaviour and no other suspicious behaviours can enter the credit service and be assessed by the model.

> The performance of the basic scorecard model has better predictive power in certain groups and consumers whose age is above 22 than under. We think that this is due to the limitation of the data by default. People under 22 don't have a central bank credit history.
> – Model developer Y

This shows that model developers attribute the weaker predictive power of the model for people under the age of 22 to the lack of associated data elements (no central bank credit history) for that group. Some predictors work better with certain groups because the models are more likely to find the most predictive characteristics among the people with more data representation.

To reiterate the crucial point: credit analytics compromise the ability of consumers with less data representation to receive credit. Although sub-models are being built to judge people from different groups, people with fewer digital traits will have less data representation in the modelling process. Minority groups are by default at a disadvantage, given that they will usually have less data for the model to learn from, or their financial limitations in the past put them in a bad position for models to evaluate. Under such a scenario, people with a data deficiency and injustice in data are disadvantaged. In the end, the model result redefines the lending access to credit based on the representation of data instead of simply safeguarding lending behaviours.

### 5.2 Credit exclusion as a result of behaviour that models cannot make inferences about

The understanding of risk also changes with time and is updated with other materialised risks. For example, materialised risks manifest themselves in evolving forms of fraudulent credit applicants. The ability to identify 'risky consumers' is developed by learning about the shared consumer behaviours by these fraudulent credit applicants. As model developer L believes, fraudulent behaviours must be similar, and consumers who exhibit these behaviours should be filtered so as to prevent similar fraud. One risky scenario that often emerges was recounted by model developer L:

> The product manager came in a hurry to the group and talked to the model developer who is responsible for developing risk strategies and modelling for their own lending product.
>
> Product manager: There is a huge wave of applicants attacking our system at 10 o'clock this morning. I think there are some suspicious applicants because yesterday there were some articles published on WDZJ saying that our credit application

> system has some loopholes. These articles have brought the above traffic to our application portal. You have to take a look at this and see how we should cope with it. This traffic has created stress for our credit enquiry portal.
>
> Model developer L: I will need to run an analysis on these applicants and see what we can do. We can update our whitelist to filter these suspicious applicants.
>
> – Fieldnote excerpt

The reason for the product manager's concern about the huge wave of applicants attacking their system was that there was a sudden large increase in credit applicants received by their platform. The increased quantification of applicants aggregated at one time-point and created stress on their credit enquiry portal, meaning that their Application Programming Interface (API) was so overwhelmed that it failed to consult with different datasets. This resulted in system errors and a paralysis of the platform, making it necessary to shut down the application portal. Since many of these applicants could have been drawn by the articles identifying the loopholes in the platform, product managers were not able to confirm whether they were good credit applicants or malicious users.

Facing this emergent circumstance, model developer L was responsible for providing counter-strategies. Model developers also strategised ways to filter consumer data for other potentials for fraud to compensate for deficiencies in identifying them. In analysing this abnormal traffic, model developer L learned that applicants had already applied for and acquired debts in many other lending platforms, enabling him to exclude all consumers with these behaviours and decline to accept their credit applications.

Credit analytics is informed by the past and evaluates the goodness of applicants' past actions (Rachels, 1991); however, it is oriented toward the future. Model developers' caution regarding behaviours shared by suspicious accounts is integrated into the technology to prohibit credit access. Once integrated into the technology, consumers are scrutinised to see if they share the same behaviours. However, the common risk events of the past may not be the common risk events of the future. In this respect, despite all the grand rhetoric about predictive power, credit analytics are fundamentally backwards-looking and, in various ways, prevent different futures from coming into being. It performatively perpetuates credit access to people that the models have learned about, as model developers proactively filter out consumers whose data is beyond the reach of the models.

### 5.3 Shaping future credit preferences through targeting and experimenting

One way forward for credit analytics to shape future lending is its ability to understand, predict and even amplify the need and demand for credit. Credit analytics in this empirical case realises this potential. Model developers use transaction data to detect when credit is needed the most. To understand this need, they run experiments by integrating consumers' real-time choices to obtain more tailored and structured data for modelling an individual's preferences. This section demonstrates the realisation of these two techniques in targeting credit consumers and amplifying the need for credit.

Big Data itself may not be informative, but it is powerful when it is paired with other datasets and tied to a real-time question. This power manifests in the potential for algorithms to link different characteristics and behaviours to denote other information such as where one goes to work, and one's most needed and desired things – and more specifically in financial services, which credit products one might have an interest in and when they are needed.

Beyond this understanding of how model developers use modelling to understand consumers, further targeting of consumers involves using certain assumptions. The impetus for developing a model to understand consumers' credit needs arises from a question asked by the operational side of the lending business: how can the application rate for credit products best be raised? While data cannot intuitively answer this question, model developers use simple logic to uncover the key elements that will lead to a desire to apply for credit. In this case, model developers incorporated their assumptions that people need credit the most when it is time to pay back other loans. As model developer L recalls:

> We were approached by the colleagues from the operational side to think of some strategies to raise the application rate of our lending product because they had observed a drop in our application of credit service after the spring festival. We were thinking, based on a simple logic, that if we can predict a period in which our users need credit most, we can then promote our product in the period when consumers need a loan most urgently.

To target consumers, model developers followed simple logic to deduce the key elements of their desire for credit. In this circumstance, model developer L thinks that the desire for credit increases when people need to repay their loans. Using the forecast time of credit repayment, model developer L asks the operational colleague to send timely marketing information to consumers.

> The large quantities of transaction data include information about users' other credit card repayment. We can see the specific data in each month that one has credit card repayment. Then we can predict a time range to target this user. In the end, the result of this response model comes back very good. We have raised our response rate to 54%.
> – Model developer L

Developer L was able to predict the time of repayment of consumers' credit cards using their payment and transactional data. He detects the patterns in the data showing a range of repetitive dates that one repays loans so as to infer a range of repayment data with the highest frequency. They call this a response model, as this model can elicit reaction and response by consumers. Eventually, this model attracted 54% more consumers to react and apply for credit. With this, credit analytics promotes the need for credit and more actively shapes lending behaviour.

Further experiments are integrated into generating more classification data to build models targeting similar consumers. With the functionality of collecting digital traces in real time, model developers combine modelling with experiments to understand consumer behaviours better. Experiments refer to the process of observing consumer choices in a controlled or manufactured environment and collecting consumer data. For this, model developers work with colleagues from operations to set up advertisements and observe their responses. Then they analyse consumers' interest in credit.

> Through this clicking response, we can classify people into two different classes: people who would be interested in such a product and people who would not be interested. Through machine learning, we will select different characteristics that are useful in differentiating these two categories. We can use this model to understand who will be interested in this type of product later and only target the consumers that would be interested in saving marketing cost.
> – Modelling supervisor

In particular, by labelling consumers' actions in a situational scenario, model developers use consumers as experimental subjects. The experiment results – in the form of a digital trace (clicked or not) – are treated as labelled data, which is later used to model characteristics predictive of consumers' preferences. If one applies for credit through that advertisement online, it is marked as 1 in the development data, and if one does not apply, it is marked as 0. Model developers assign this label and match this information with the other characteristic data in their dataset to predict which consumers will have similar preferences.

In an attempt to reduce the cost of online marketing, model developers use predictor characteristics to select consumers with similar preferences. Thus, advertisements are released only to those consumers with the predicted preference. Through such experimentation, model developers can build further models to emulate credit preferences, amplifying the potential volumes of credit applications.

Overall, these approaches to understanding through modelling and experimentation and the emulation of consumer preferences enable the subtle targeting of consumers and further shape the desire for credit service. The historical presence of access to credit is reproduced through this intentional targeting. Credit technology in this setting has the capacity to reproduce and consolidate consumer preferences for credit. Consumers who are more likely to have more credit are targeted for applying for more. In this sense, credit analytics holds a proactive and transformative ability to drive desires in credit service, consolidating the overall structure of credit access.

## 6. Discussion

With calculation and quantitative measures becoming more widespread, Mennicken and Espeland (2019) call for further examination of the interactions between different quantification regimes. Credit technology provides credit assessment measures and cuts across the regime of quantification in economisation (Carruthers, 2013; Poon, 2009) and in personal life (Fourcade and Healy, 2017). Moreover, in line with Mehrpouya and Samiolo (2016) and Pollock and D'Adderio (2012), this paper explores the production side of a quantitative measure. However, in contrast with previous literature, we examine the roles played by Big Data and algorithmic machines in the production of a quantitative measure in more depth. Our research traces the specific material, technological and human configurations of modelling work (Knuuttila et al., 2006).

In delivering financial inclusion, fintech companies rely on algorithms to measure lending risk and make lending decisions. However, the algorithms themselves do not have a predefined concept of creditworthiness. Model developers use Big Data and machine learning to configure credit models and develop strategies that lay down the initial starting point for instilling the concept into algorithms. During this process, the modellers' choices, such as what to choose as variables, are informed by the calculative culture that they operate within. Therefore, we examine the calculative culture through the modellers' choices in configuring credit models and evaluate the consequences of this culture and the performative effect of credit technology on credit access.

### 6.1 Reductive calculative culture and the pursuit of high statistical model performance

This paper demonstrates model developers' belief in the promise of machine learning algorithms and Big Data. It shows that the rather notion of creditworthiness has been reduced and rely on the judgement of statistical significance from complex social factors. With quantified model objectives, the model intention was set to recognise 'good' and 'bad' accounts as simplified and clear-cut statistical numbers. Model developers rely on statistical and machine learning algorithms, and they focus on the pursuit of high statistical model performance. In this, data quality and quantity become crucial in determining who is more creditworthy, and who is not. As a result, it argues that credit modelling work is confined within an 'algorithmic cage', where modellers give way to the statistical representation of data in deciding what to measure.

Being in the algorithmic cage, modellers' 'epistemic work' (Mehrpouya and Samiolo, 2016) is limited by the statistical representation of Big Data. Yet, especially in the use of machine learning algorithms, humans cannot intuitively understand the calculating process. Through non-transparent machine learning, model developers do not accumulate knowledge to understand the notion of creditworthiness. In effect, model developers are again repetitively confined in building the models and rely on machine learning algorithms. Likewise, it is debatable whether humans are still the 'trusted agencies' (MacKenzie, 2001, p. 12) who can account for what is built in the machine.

Moreover, modellers' understanding of the world and reality is thereby constrained by a world that is measured and stored in a dataset; data as modelling material determines the range of what model developers see. Furthermore, the statistical correlation becomes a strict assessment criterion for deciding on predictors for future evaluation and, therefore, modelling results are confined by the model efficacy and its statistical injustice.

I argue that the practice of relying on algorithmic software and data representation as epistemic tools (Knuuttila and Merz, 2009; Knorr Cetina, 1997, 2001; Rheinberger, 1997) is more 'culture-dependent' and 'culture-driven'. Informed by the 'evaluation culture' of MacKenzie and Spears (2014b), I see that, when the same practice, inspired by the same culture, is potentially shared within the same community across other organisations, it becomes a wider phenomenon. In this empirical case, using KS as the main indicator of model performability is a result of other institutes across the financial industry in China using it.

However, prior research in the calculative culture of model use (e.g., Hansen, 2020) has focused on surveying practitioners' attitudes towards financial models. Our research offers a more comprehensive overview of the construction of credit models. Rather than staying in the two camps of attitudes, i.e. pragmatic or idealistic calculative cultures (Power, 2007), the findings address a calculative culture that is underpinned by a narrow focus on high statistical model performance. This study alerts us to the need for practitioners to devote attention to the calculative culture of the organisation to avoid modelling in an algorithmic cage. They should also be aware of the calculative culture of their organisations, so as to ensure quality control of the production of algorithms.

### 6.2 Performativity and proactiveness

This study points to ways of furthering understanding of how credit analytics performatively shapes our credit access in the future. As Callon (1998, p. 23) phrases it: ‘calculativeness couldn’t exist without calculating tools’. It focuses on the credit modelling practices that, as an outcome, produce financial exclusion. With this emphasis, it addresses how credit technology escalates from simply shaping the future through predicting a performativity of ‘proactiveness’, whereby calculative practice updates its ability to understand and even to proactively amplify the need and demand for credit that perpetuates the structure of credit access.

Our findings show that modellers exclude consumers from online credit access when models cannot evaluate them. Operating in an online environment, the limited efficacy of credit models can increase the lending risk to a high level. To obtain the level of quality assurance of debts, modellers come up with more strict safeguarding policies when their digital infrastructure reaches a larger population – they filter out consumers with intuitively suspicious behaviour and behaviours about which the model cannot make inferences.

In addition, I observe that modellers conduct experiments with consumers to gain more data, strengthening the power of their targeting methods. Specific targeting through learning about consumers’ preferences enables modellers to optimise their advertising resources and channels better. As a result, modellers provoke (Muniesa, 2014) consumers in need of credit to end up needing more credit while blocking those who are not thinking about credit at that time from learning about available opportunities. In response, this condition further perpetuates the structure of financial access to credit because consumers who have taken more credit services will have more data available for the data presentation in credit scoring.

The integration of real-time experiments with consumers further generates digital traces that can be used in modelling. This highlights the fact that Big Data modelling has a different epistemological power than traditional economic modelling. Before Big Data, traditional economic models and experiments were considered separately as two of the most common means to examine the economic world. Morgan (2005) prefers experiments over economic modelling, explaining that models are built from elements of theory, elements of data and analogical elements (Morgan and Morrison, 1999); the development of a model constructs an 'artificial world', creating a contrast when this 'artificial world' meets 'the real one' of people and economic decisions, whereas experiments are versions of the real world framed in an artificial laboratory environment. Morgan infers that experiments have greater epistemological power. In contemporary modelling, these methods are combined, meaning that modellers can proactively interact with reality and modify its structure.

Previous research on credit scoring shows that credit scoring cannot survive the interrogation of fairness due to its moral limits (Kiviat, 2019). Langevin (2019) has also shown that microlending platforms can be motivated by the agenda to gain profit, which drives debtors into more debt. In the current discussion of digital technology extending financial inclusion, I present a case where practices that do not eliminate algorithmic injustice create a new form of financial exclusion. In line with other studies (Eubanks, 2019; Gensler and Bailey, 2020; Wachter-Boettcher, 2017) that critique algorithmic injustice and fairness, our research shows that the configuration of technology does not fix algorithmic injustice; on the contrary, it sustains the algorithmic injustice and even intensifies injustices by creating exclusion.

Future work can explore the conditions that will produce a counter-performativity effect (MacKenzie, 2007) of credit models. Boedker et al. (2020) describe that ranking systems are not inherently performative and that there are conditions (Callon, 2010) that can give rise to resistance, producing a counter-performativity effect. Therefore, further research that captures the ‘felicity conditions’ for resistance to forming model performativity or that proposes an alternative calculative culture from the one explored in this study is needed to prevent the effect of algorithmic injustice.

## 7. Conclusion

This research is based on the credit scoring centre of a large internet company in China, where credit scoring utilises multiple dimensions of personal data. The company uses the credit score result produced by the models in its automated online micro-lending products and has built a basic scorecard model to issue credit scores for the whole population of China. Our research explores this calculative agent to understand how the quantification of economics affects personal life, where model developers are ceding more and more authority to machines.

This research opens the black box of how credit models are created, having a peek in the production of automated algorithms. My ethnographic data shows how choices of model variables are ‘learnt’, and the consumer quality leading to credit default is ‘seen’ through the practice of credit modelling. It disclose the modeller’s ideation and beliefs behind their technological configuration. Through this, this paper contributes to a closer understanding of the algorithmic production of consumers’ creditworthiness.

We propose to extend the discussion on financial exclusion by drawing attention to the results of algorithmic injustice perpetuated by credit modelling in a algorithmic cage'. We explore the specific modelling culture, which gives rise to injustice, instead of eliminating them. The advancement of technology is constant; however, the technological arrangements in calculative practice are cultural.

This paper contributes to the literature in two ways: in calculative culture and performativity of Big Data credit models. We contribute to the understanding of calculative cultures in affecting the production of an algorithmic measure in this ever-increasing 'algorithmic economy' (Bamford and MacKenzie, 2018) in 'surveillance capitalism' (Zuboff, 2019). Moreover, we examine how injustice emerges in the modelling process and provide an understanding of how experiments and targeting are being used by modellers to further shape access to credit.

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# V. Conclusion

## 1. Overview

In exploring the development of credit modelling in a major internet company in China, this thesis examines the configuration of Big Data algorithmic credit scoring. The three empirical chapters respectively reveal the organisation of data science work, modelling challenges, limitations and organisational innovation, compliance and struggles in delivering the technology that the political programme seeks to achieve. In addition, the thesis brings to light the overall permeating calculative culture within which model developers operate. It also demonstrates the impact of cultural/epistemic factors, such as credit modelling in an algorithmic cage and algorithmic injustice, on financial exclusion.

The first empirical chapter extends the discussion of 'technological affordance' (Leonardi, 2011; Zammuto et al., 2007) to consider the negative outcome when overlooking social and organisational elements. The findings of this chapter demonstrate the development procedures of Big Data credit scoring models and the challenges surrounding its relevant components, such as data, algorithms, outputs and key performance indicators. Organisational arrangements facilitating these components in turn have caused organisational struggles for data science work. The findings further show that the current way of organising Big Data credit scoring models to follow a standardised procedure converts highly skilled work into a process of performing simpler tasks. Therefore, the nature of modelling work is constrained and often limited to deploying existing knowledge to prepare data and run pre-prescribed procedures.

The second empirical chapter analyses links between political aspirations and technological implementation via organisations. The findings show the local rendering processes which results in different ways of understanding creditworthiness that shapes the technology differently. When the macro-level rationality of a political programme remains broad and distanced, various micro-level factors need to be accounted for in local design and implementation. The findings show that sensemaking, strategising and strategic adaptation are utilised as important organisational processes both prior to and during the development of technology, where these organisations further use programmatic discourses to support what they strategically aim to achieve and build. Organisations render their dispositions, and further take in account the state holders' need in navigating their technological development. The organisations studied here seem to alter the government programme to attain their own goals and further enhance organisational capability, as the organisations use political programmes to conduct credit reporting for product optimisation, creating an invasive impact on consumers' lives.

The third empirical chapter responds to recent calls to increase the use of advanced credit lending technologies to address financial inclusion. In this chapter, I contend that credit modelling is as a result being placed in a algorithmic cage. This cage sets boundaries to modelling that underpin statistical significance. The model developers cannot look beyond the statistical numbers that make up the cage to discover the full complexity of the concepts being modelled. Algorithmic injustice is not eliminated because the imperfect condition of the data becomes the full picture of reality for the developers. Moreover, the model struggles to evaluate certain consumers due to insufficient data, resulting in them being filtered out from access to credit. Consequently, this data bias hinders financial inclusion. The findings have also shown the proactiveness of credit technology in shaping credit needs. For instance, model developers conduct experiments to obtain consumer data to further target certain groups of consumers (which further stimulates the need for credit).

Overall, by outlining the practices and articulating the meso-level dynamics that affect the enactment of the Chinese state's aspirational programme of building a social credit system, the study shows the various mechanisms through which state aspirations at the macro level are made intelligible and brought to life. In an era of Big Data and ever-increasing surveillance, this research reveals that the beliefs held about Big Data, and the specific organisational work processes in the field of data science - employed to locate statistical significance and model predictability - lead to the relentless acquisition of personal data and the production of contestable measures of creditworthiness.

## 2. Implications: Are we 'there' yet?

When commenting on the current hype of machine learning and artificial intelligence (AI), computer scientists Marcus and Davis (2019) use the phrase 'mind the gap' (p.12) to warn us that we should not overestimate what can be accomplished with machine learning and AI. Alongside an ethnographic account, this thesis addresses the ideational (or social) and material configurations (Bertucci et al., 2018) of these technologies and highlights the important role played by model developers who work to implement these technologies at the operational level. The findings of this thesis inform us of the challenges ahead in the gap of achieving a 'safe, smart and reliable AI' (Marcus and Davis, 2019, p.44).

The first finding shows data science work as continuous and repetitive and emphasises the contrast between the mundane work of preparing data and configuring models and the intelligent and automated way these technologies were imagined. The material and the technical conditions bring structure to how model developers work as they are required to comply with material and technical constraints. When envisioning more of these technological functions in future work (Orlikowski, 2000), we can see the workflow structure that is brought about by the material and technical elements embedded in technological implementation and these material and technical elements becomes more important in organisational life, as evidenced in the struggle of data scientists constantly fighting for data.

We currently face the challenge of organising data science operations more effectively, that further impacts organisational decision making (Hodson, 2016). The findings invite a reconsideration of the evaluation of key performance indicators that incentivise and motivate the field of data science and suggests a different way of organising operations at scale. As model performance is tightly coupled with available data, this alternative method of organisation creates a fight for data as a scarce and protected resource. This suggests that managers should develop strategies to avoid perverse incentives, monotony of work, and to find ways of breaking data silos within and between organisations.

When a large state programme tries to mobilise organisational innovation to create progress in science and technology, some organisations, through local rendering, adapt the state programme to align with their own strategic visions. Therefore, regulators who are designing state projects should be aware of the unintended consequences that exist when transmitting and delivering political rationales over long distances.

Moreover, when algorithmic measures are devised to govern, their design and implementation are blended in with political rationales and organisational agendas. We may want to understand what such algorithmic processes actually measure. In this thesis, we uncover a localisation process used by organisations wherein the differences in local resources and organisational dispositions create heterogeneous results in the algorithmic measures.

Society is still working to find a way to ensure algorithmic fairness before proceeding down the dangerous trajectory of using highly automated algorithmic results. The findings of this thesis demonstrate a reductive calculative culture that leads to credit modelling in an algorithmic cage where the complex notion of creditworthiness becomes a matter of statistical significance. Given such a culture, model developers cede more authority to statistical results, which, in turn, give way to biased data representation (or inputs). If we cannot open the black box of proprietary algorithms, we can propose adjustments for an alternative calculative culture that considers algorithmic injustice as likely omnipresent.

The findings of this thesis show that data is not only collected but also generated through experiments and increasing productisation. The integration of real-time experiments with consumers further generates digital traces that can be used in modelling. Prior to the availability of Big Data, traditional economic models and experiments were considered separately as two of the most common means of examining the economic world (Morgan, 2015). Now, experiments create more data for models to use. Our current trajectory suggests an ever-increasing amount of data available for modelling, either through passive collection or active generation. Are there ethical concerns as to how this data is generated? More scholarly research is needed to delve into this direction.

## 3. Contributions

This thesis challenges the idea that Big Data credit scoring is inclusive, objective and comprehensive. It emphasises the fact that the nuanced details of data preparation and model configuration (i.e. setting model objectives, running statistical algorithms) and the managerial organisation of modelling work can influence the results of Big Data credit scoring. I argue that this thesis makes the following four contributions:

First, its findings provide an ethnographic account of strong organisational-level evidence regarding the production of algorithmic models. This thesis remedies the gap in our understanding of the configuration of technological work in algorithmic practice. It examines the various critical factors influencing the design, usability and outcome of the models. These findings provide more details about long-term concerns relating to the black box of algorithms.

Second, we ask that more attention be given to the importance of understanding the social influences that shape affordances. Affordance is an increasingly important concept to understand in the use of AI in an organisation. How people see affordance has a direct impact on how technology is implemented, as their perception of artificial intelligence is often shaped by social, political, organisational, and individual factors. This thesis proffers the concept of organisational fallibility as a key factor in problematising the implementation of digital affordance and shows that organisational realities may lead to negative consequences that better inform data science work.

Third, this thesis traces the meso-level mechanisms that impact the development of calculative practices and seeks to understand the linkage between state programmes and those practices. As governmentality literature on calculative technologies cannot be macro- or micro-centred (Whittington, 2011), this thesis complements the governmentality framework by adding the concepts of meso-level rendering of local resources and disposition to its theoretical portmanteau.

Fourth, this thesis contributes to an understanding of the reductive calculative culture that turns the measurement of creditworthiness into a simple judgment of statistical significance and shows how biased data emerges and frames future access to credit. Moreover, this research alerts future quality control processes around algorithm production to potential new sources of injustice.

## 4. Limitations and future research

This thesis is built on the evidence of the construction of a state programme in a Chinese context. An obvious limitation of this research is that the ethnographic account and all primary interviews were conducted in China.

On our way to a more just data-driven AI society, additional research can be informed by the implications of this research.

A fruitful extension of this research may be found by examining how the concept of local rendering applies to other situations, such as other cultural settings or environments in which governments have used different methods or instruments to mobilise various institutions and fulfil their political aspirations.

Due to the organisational fallibility made evident in this research, there is a clear need for further investigation and insight into the social shaping of technological affordance. Future research could also explore the conditions that produce a counter-performativity effect on credit models and capture the conditions for resistance to forming model performativity. Another interesting extension of this work may be to study an alternative calculative culture from the one explored in this study; one that may prevent the effects of algorithmic injustice.

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## Appendix I

Table 4. Eight companies with their different proprietary data

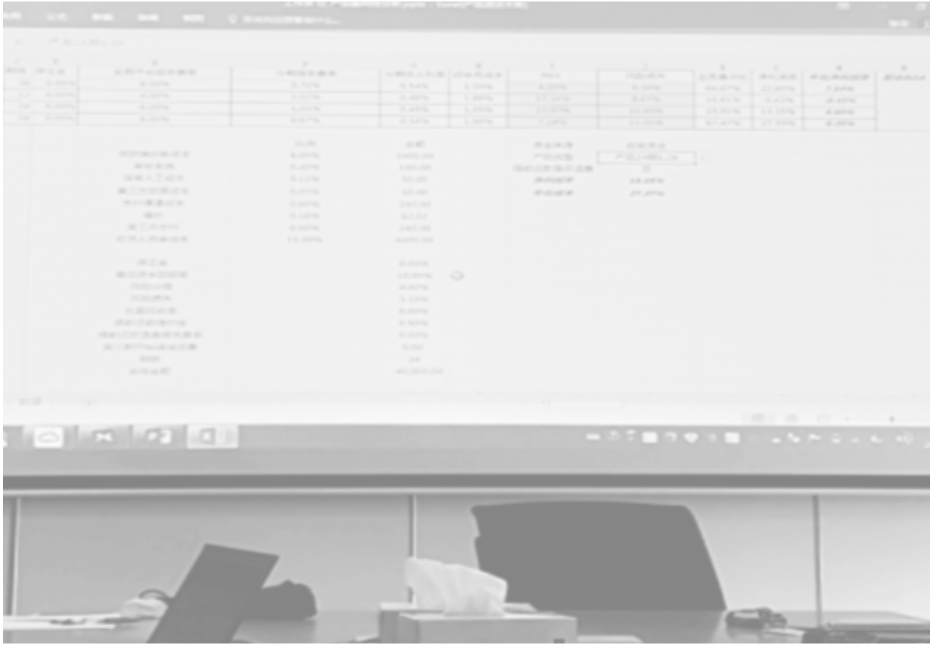
| | |
|---|---|
| Company 1 | Partnership with around 250 internet finance P2P lending companies' data |
| Company 2 | Partnership with banks, micro-lending companies, online shopping data |
| Company 3 | Payment data (online payment data), education data, bank data |
| Company 4 | Social network data（Wechat）, behavioral data (service data), payment data, finance product data |
| Company 5 | Behavioral data (Taobao), payment data (Alipay), consumption data, financial product data |
| Company 6 | Consumption data (JD Mall), telephone data (how long one has used the number), air ticket data (what class flight) |
| Company 7 | Insurance data and other financial data of its mother group |
| Company 8 | Education data, bank data, investment data |

## Appendix II

Samples of materials and data collected in the field:

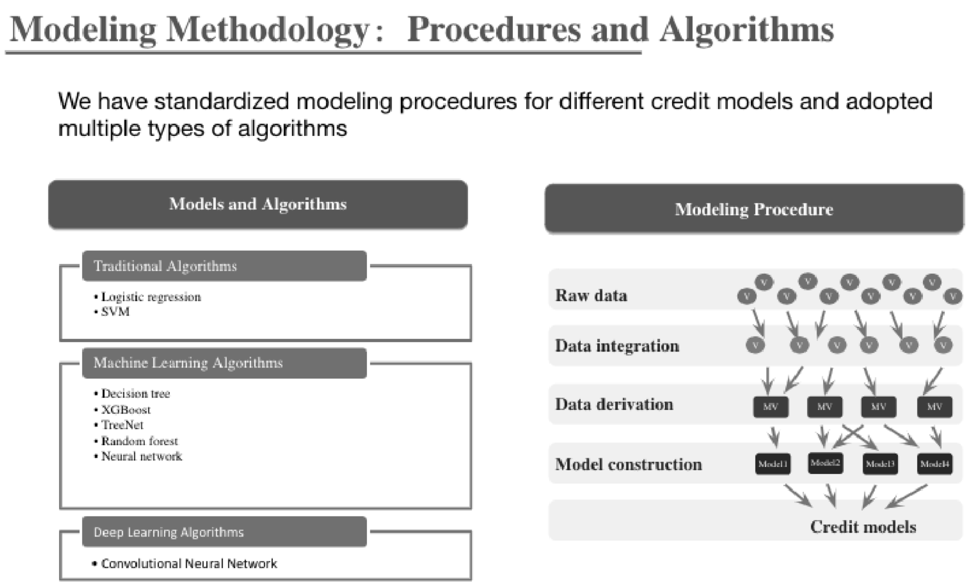
Picture 1. The author observes credit modelling team's weekly meeting

Picture 2. Model developers use Excel to go through the statistical significance of variables in a weekly meeting



Picture 3. The author’s working desk in the office of the CSC

Picture 4. A sample of internal PowerPoint slide on modelling methodology



Picture 5. A sample of hand-written fieldnotes