

1 **Operational Framework: Institutional Controls - The New Deal** 2 **on Data**

3 Daniel "Dazza" Greenwood^{1,*}, Arkadiusz Stopczynski^{1,2}, Brian Sweatt¹, Thomas Hardjono¹,
4 Alex Sandy Pentland¹

5 **1 MIT**

6 **2 DTU**

7 * **E-mail: dazza@civics.com**

8 **Contents**

9	1 Introduction (Arek)	2
10	2 The New Realities of Living in a Big Data Society (Arek)	2
11	3 The New Deal on Data (Arek)	4
12	4 Personal Data: Emergence of a New Asset Class (Thomas)	6
13	5 Enforcing the New Deal on Data (Dazza)	10
14	6 Transitioning End-User Assent Practices (Arek)	13
15	7 Business, Legal, and Technical Dimensions of Big Data Systems (Dazza)	15
16	8 Big Data and Personal Data Institutional Controls (Thomas)	16
17	9 Scenarios of Use in Context (Dazza)	21
18	9.1 Example Scenario: Research Systems	21
19	9.2 Scenarios of Use Today, Tomorrow and the Day After	24
20	10 Future Research (Brian)	26
21	10.1 Research on Design and Deployment of Big Data Systems	27

22	10.2 Research on Big Data for Design of Institutions	29
----	--	----

23	11 Conclusions	31
----	-----------------------	-----------

24 **1 Introduction (Arek)**

25 To realize the promise and prospects of a Big Data society and avoid its security and confiden-
 26 tiality perils, institutions are updating operational frameworks governing business, legal, and
 27 technical dimensions of their internal organization and interactions with the outside world. This
 28 chapter describes how the common good can be served by framing these types of institutional
 29 rules and processes to ensure a greater user control over personal data, as well as large scale risk
 30 management and interoperability for data sharing between and among institutions.

31 The control points traditionally relied upon as part of corporate governance, management
 32 oversight, legal compliance, and enterprise architecture must evolve and expand to match op-
 33 erational frameworks for Big Data. An operational framework used for a Big Data-driven or-
 34 ganization requires a balanced set of institutional controls. These institutional controls must
 35 support and reflect greater user control over personal data and large scale interoperability for
 36 data sharing between and among institutions. Core capabilities of these controls include re-
 37 sponsive rule-based systems governance and fine-grained authorizations for distributed rights
 38 management. In the following sections we explore the emergence of the Big Data Society, out-
 39 line the ways to support it in the institutional context, and draft the future directions of research
 40 and development.

41 **2 The New Realities of Living in a Big Data Society (Arek)**

42 Sustaining a healthy, safe, and efficient society is a scientific and engineering challenge going
 43 back to the 1800s, when the Industrial Revolution spurred rapid urban growth, creating huge
 44 social and environmental problems. The remedy then was to build centralized networks that
 45 delivered clean water and safe food, enabled commerce, removed waste, provided energy, fa-

46 cilitated transportation, and offered access to centralized healthcare, police, and educational
47 services. Those networks formed the backbone of the society as we know it today.

48 These century-old solutions are however becoming increasingly obsolete and inefficient. We
49 have cities jammed with traffic, world-wide outbreaks of disease that are seemingly unstoppable,
50 and political institutions that are deadlocked and unable to act. We face the challenges of global
51 warming, uncertain energy, water, and food supplies, and a rising population and urbanization,
52 that will add 350 million people to the urban population by 2025 in China alone [14].

53 It does not have to be this way. We can have cities that are protected from pandemics, energy
54 efficient, have secure food and water supplies, and have much better government. To reach these
55 goals, however, we need to radically rethink our approach. Rather than static fixed systems,
56 separated by function — water, food, waste, transport, education, energy — we must consider
57 them as dynamic, data-driven networks. Instead of focusing only on access and distribution,
58 we need the networked and self-regulating systems, driven by the needs and preferences of the
59 citizens. We also need to create the channels for the society to agree upon and communicate
60 those needs.

61 To ensure a sustainable future society, we must use our new technologies to create a *nervous*
62 *system* maintaining the stability of government, energy, and public health systems around the
63 globe. Our digital feedback technologies are today capable of creating a level of dynamic re-
64 sponsiveness that our larger, more complicated modern society requires. We must reinvent the
65 systems of the societies within a control framework: sensing the situation, combining these obser-
66 vations with models of demand and dynamic reaction, and finally using the resulting predictions
67 to tune the system to match the demands.

68 The engine driving this new nervous system is Big Data: the newly ubiquitous digital data,
69 now available about all aspects of human life. We can analyze patterns of human experience and
70 ideas exchange within the *digital breadcrumbs* that we all leave behind as we move through the
71 world: call records, credit card transactions, GPS location fixes, among others. By recording
72 our choices, these data tell the story of our lives. And this may be very different from what

we decide to put on Facebook or Twitter; our postings there are what we choose to tell people, edited according to the standards of the day and filtered to match the persona we are building. Mining social networks can give some great insights about human nature [4, 26, 40]; who we really are is however even more accurately determined by where we spend our time and which things we buy, rather than just what we say we do [25].

The process of analyzing the patterns within these digital breadcrumbs is called reality mining [13, 30], and through it we can learn an enormous amount about who we are. The Human Dynamics research group at MIT have found that we can use them to tell if we are likely to get diabetes [31], or whether we are the sort of person who will pay back loans [32]. By analyzing these patterns across many people, we are discovering that we can begin to explain many things — crashes, revolutions, bubbles — that previously appeared to be random acts of God [28]. For this reason the magazine *Technology Review* named our development of reality mining as one of the ten technologies that will change the world [16].

3 The New Deal on Data (Arek)

The digital breadcrumbs we leave behind provide clues about who we are, what we do and want. This makes these personal data immensely valuable, both for public good and for private companies. As European Consumer Commissioner, Meglena Kuneva said recently, “Personal data is the new oil of the Internet and the new currency of the digital world” [21]. This new ability to see the details of every interaction can be however used for good or for ill. Therefore, maintaining protection of personal privacy and freedom is critical to our future success as a society. We need to enable even more data sharing for the public good; at the same time, we need to do a much better job in protecting the privacy of the individuals.

A successful data-driven society must be able to guarantee that our data will not be abused; perhaps especially that government will not abuse the power conferred by access to such fine-grain data. To achieve the positive possibilities of the new society, we require the *New Deal on Data*, workable guarantees that the data needed for public good are readily available while at

99 the same time protecting the citizenry [30]. For this, we must develop much more powerful and
100 sophisticated tools to use personal data to both build a better society and to protect the rights
101 of the citizens.

102 The key insight that motivates the idea of the New Deal on Data is that our data are worth
103 more when shared, because these aggregated data inform improvements in systems such as
104 public health, transportation, and government. For instance, we have demonstrated that data
105 about the way we behave and where we go can be used to minimize the spread of infectious
106 disease [24, 31]. Our research has reported how we were able to use these digital breadcrumbs
107 to track the spread of influenza from person to person on an individual level. And if we can see
108 it, we can stop it.

109 Similarly, if we are worried about global warming, these shared, aggregated data can show
110 us how patterns of mobility relate to productivity [29]. In turn, this provides us with the ability
111 to design cities that are more productive and, at the same time, more energy efficient. But in
112 order to be able to obtain these results and make a greener world, we need to be able to see
113 the people moving around; this depends on many people willing to contribute their data, even
114 if only anonymously and in aggregate.

115 While concrete examples such as better health systems and more energy efficient transporta-
116 tion systems motivate the New Deal on Data, there is an even greater public good that can be
117 achieved by efficient and safe data sharing. To enable sharing of personal data and experiences,
118 we need secure technology and regulation that allow individuals to safely and conveniently share
119 personal information with each other, with corporations, and with government. Consequently,
120 the heart of the New Deal on Data must be to provide both regulatory standards and financial
121 incentives that entice owners to share data, while at the same time serving the interests of both
122 individuals and society at large. We must promote greater idea flow among individuals, not just
123 corporations or government departments.

124 Unfortunately, today most personal data are siloed off in private companies and therefore
125 largely unavailable. Private organizations collect the vast majority of the personal data in the

form of mobility patterns, financial transactions, phone and Internet communications. These data must not remain the exclusive domain of private companies, because then they are less likely to contribute to the common good. These private organizations must be thus the key players in the New Deal on Data framework for privacy and data control. Likewise, these data should not become the exclusive domain of the government, as this will not serve the public interest of transparency; we should be suspicious of trusting the government with such power. Ultimately, the entities who should be empowered to share and make decisions about their data, are people themselves: users, participants, citizens.

The ultimate goal is to provide the society with tools to analyze and understand what needs to be done, and to reach the consensus on how to do it. This goes beyond just creating more communication platforms. The assumption that more interactions between users will result in better decisions being made, may be very misleading. Although in the recent years we have seen some great examples of using social networks for better organization in society, for example during political protests [6, 17], we are not even close to the point where we can start reaching consensus about the big problems: epidemics, climate change, pollution. The discussions must be data driven, involving both experts and wisdom of the crowds, users themselves interested in improving the society. The problems we are dealing with as a now global society are not easy. We are responsible for many of them, and being able to tackle them on a global scale is necessary for our, mankind, survival.

4 Personal Data: Emergence of a New Asset Class (Thomas)

It has long been recognized that the first step to promoting liquidity in land and commodity markets is to guarantee ownership rights so that people can safely buy and sell. Similarly, the first step toward creating greater idea and idea flow ('idea liquidity') is to define ownership rights. The only politically viable course is to give individual citizens rights over data that are about them and in fact, in the European Union these rights flow directly from the constitution **AS:**
Citation? There is no 'EU constitution' per se. . We need to recognize personal data

152 as a valuable asset of the individual that is given to companies and government in return for
 153 services.

154 The simplest approach to defining what it means to own your own data is to draw an analogy
 155 with the English common law ownership rights of possession, use, and disposal:

- 156 • You have the right to possess data about you. Regardless of what entity collects the data,
 157 the data belong to you, and you can access your data at any time. Data collectors thus
 158 play a role akin to a bank, managing the data on behalf of their customers.
- 159 • You have the right to full control over the use of your data. The terms of use must be opt-
 160 in and clearly explained in plain language. If you are not happy with the way a company
 161 uses your data, you can remove the data, just as you would close your account with a bank
 162 that is not providing satisfactory service.
- 163 • You have the right to dispose of or distribute your data. You have the option to have data
 164 about you destroyed or redeployed elsewhere.

165 Individual rights to personal data must be balanced with the need of corporations and govern-
 166 ments to use certain data-account activity, billing information, and so on-to run their day-to-day
 167 operations. This New Deal on Data therefore gives individuals the right to possess, control, and
 168 dispose of copies of these required operational data, along with copies of the incidental data
 169 collected about you such as location and similar context.

170 Note that these ownership rights are not exactly the same as literal ownership under modern
 171 law, but the practical effect is that disputes are resolved in a different, simpler manner than
 172 would be the case for (as an example) land ownership disputes.

173 In 2007, one author (Pentland) first proposed the New Deal on Data to the World Economic
 174 Forum [41]. Since then, this idea has run through various discussions and eventually helped
 175 shape the 2012 Consumer Data Bill of Rights in the United States, along with a matching
 176 declaration on Personal Data Rights in the EU. These new regulations hope to accomplish the
 177 combined trick of breaking data out of the current silos, thus enabling public goods, while at

178 the same time giving individuals greater control over data about them. But, of course this is
 179 still a work in progress and the battle for individual control of personal data rages onward.

180 The World Economic Forum (WEF) has dubbed personal data as the “New Oil” or resource
 181 of the 21st century [41]. The discovery of oil and the subsequent development of the oil industry
 182 over the past 100 years has spurred not only the development of the automobile industry but also
 183 the creation of the global transportation infrastructure, including the massive freeway networks
 184 that we see today in the developed nations. The “personal data sector” of the economy today is
 185 still in its infancy, its state akin to the oil industry at the late 1890s prior to the development of
 186 the Model-T Ford automobile. The productive collaboration between the Government (building
 187 the state owned freeways), the private sector (mining and refining oil, building automobiles) and
 188 the citizen (the user-base of these services) allowed the developed nations to expand its economies
 189 by creating new markets adjacent to the automobile and oil industries.

190 If personal data, as the new oil, is to reach its global economic potential, there needs to be
 191 a productive collaboration between all the stakeholders in the establishment of a *personal data*
 192 *ecosystem*. As mentioned in [41], a number of fundamental questions about privacy, property,
 193 global governance, human rights – essentially around who should benefit from the products and
 194 services built upon personal data – are major uncertainties shaping the opportunity. The rapid
 195 rate of technological change and commercialization in using personal data is undermining end
 196 user confidence and trust.

197 The current personal data ecosystem is fragmented and inefficient. Too much leverage is
 198 currently being accorded to service providers that on-board and register end-users. These siloed
 199 repositories of personal data exemplifies the fragmentation of the ecosystem. These repositories
 200 contain data of varying qualities. Some are attributes of persons that are unverified, while
 201 other represent higher quality data that have been cross-correlated with other data points of the
 202 end-user.

203 For many participants, the risks and liabilities exceed the economic returns. Besides not
 204 having the infrastructure and tools to manage personal data, many end-users simply do not see

the benefit of fully participating in the ecosystem. The current focus of many Internet-based service providers is to capture as much personal data from the end-user and to sell this data into the advertising industry. Personal privacy concerns are thus inadequately addressed at best, or simply overlooked in the majority of the cases. The current technologies and laws fall short of providing the legal and technical infrastructure needed to support a well-functioning digital economy.

Recently, we have shown how challenging, but also feasible, it is to open such institutional Big Data. In the Data For Development (D4D) Challenge <http://www.d4d.orange.com/home>, the telecom operator Orange opened access to a large dataset of call detail records (CDRs) from the Ivory Coast. Working with the data as part of a challenge, teams of researchers came up with life-changing insights for the country. For example, one team developed a model for how disease spread in the country and demonstrated that information campaigns based on one-to-one phone conversations among members of social groups can be an effective countermeasure [23]. In releasing and analysing this data, the privacy of the people who generated the data was protected not only by the technical means, such as removal of the Personally Identifiable Information (PIIs), but also by legal means, with the researchers signing an agreement they will not use the data for re-identification or other nefarious purposes. As we have seen in several cases, such as the Netflix Prize privacy disaster [27] and other similar privacy breaches [35], true anonymization is extremely hard. In the Unique in the Crowd [10], de Montjoye et al. showed that even though human beings are highly predictable [33], we are also very unique. Having access to one dataset, it may be easy to uniquely fingerprint someone based on just few datapoints, and use this fingerprint to discover their true identity. The higher the resolution of the data, the easier it gets to identify a person from this type of data.

The report of the World Economic Forum [41] also suggest a way forward by recommending a number of areas where efforts could be directed:

- Alignment of key stakeholders: Citizens, the private sector and the public sector need to work in support of one another. Efforts such as NSTIC [36] – albeit still in its infancy –

represents a promising direction for a global collaboration.

- Viewing “data as money”: There needs to be a new change in mindset where an individual’s personal data items are viewed and treated in the same way as their money. These personal data items would reside in an “account” (like a bank account) where it would be controlled, managed, exchanged and accounted for just like personal banking services operate today.
- End-user centricity: All entities in the ecosystem need to recognize that end-users are vital and independent stakeholders in the co-creation and value exchange of services and experiences. Efforts such as the *User managed Access* (UMA) initiative [2] point in the right direction by designing systems that are user-centric and managed by the user.

Opening data from the silos by publishing static datasets is important, but it is only the first step. We can do even more substantial things when the data is available in real time and can become part of a society’s nervous system. Epidemics can be monitored and prevented in real time [31], underperforming students can be helped, and people with health risks can be treated before they get sick [9]. The same data can potentially be used for stalking, burglarizing one’s home, and as justification to charge people more for an insurance policy.

5 Enforcing the New Deal on Data (Dazza)

How can we enforce this New Deal? The threat of legal action alone is important, but insufficient, because if you cannot see abuses then you cannot prosecute them. Moreover, who wants more lawsuits anyway? Enforcement can be addressed in significant ways without prosecution of public statute or regulation at all. In many fields, companies and governments rely upon multi-party frameworks of agreed rules governing common business, legal, and technical practices to create effective self-organization and enforcement. These approaches hold promise as a method for using institutional controls to form a reliable operational framework balancing the needs for big data, privacy, and access.

One current best practice is a system of data sharing called trust networks. Trust networks are a combination of networked computers and legal rules defining and governing expectations regarding data. With respect to data belonging to individuals, these networks of technical and legal rules keeps track of user permissions for each piece of personal data, and a legal contract that specifies both what you can and cannot do with the data and what happens if there is a violation of the permissions. For example, in such a system all personal data can have attached labels specifying what the data can and cannot be used for. These labels are exactly matched by the network's system rules and terms in legal contracts between all the participants, stating penalties for not obeying the permission labels. These rules can, and often do, reference or require audits of relevant systems and data use, demonstrating how traditional internal controls can be leveraged as part of the transition to more novel trust models.

Complete tracking and regulation of every aspect of a trust network is not the goal or even desirable in order to achieve effective enforcement. Rather, the rules for a trust network align enforcement with the highest priority issues and those upon which trust of participants is premised. The relevant issues arise from the dynamics of data flows, underlying trust models, and contextual scenarios within which the networked data and the relationships of parties in the trust network **AS: This sentence is hard to understand. Missing verb?** . When a trust network involves use of personal data, then the user permissions and corresponding limits on use are fundamental to the trust model. In this context, the permissions, including the provenance of the data, should require appropriate levels of audit. A well designed trust network, elegantly integrating computer and legal rules, allows automatic auditing of data use and allows individuals to change their permissions and withdraw data.

Having system rules applicable to the networks, applications, and data as well as all the services providers other intermediaries, and the users themselves is the mechanism for establishing and operating a trust network. System rules are sometimes called operating regulations in the credit card context, or known as trust frameworks in the identity federations context, or trading partner agreements in a supply value chain context. There are many general examples of

283 multiparty shared architectural and contractual rules that share the generic characteristic of cre-
284 ating binding obligations and enforceable expectations on all participants in scalable networks.
285 Another common characteristic of the system rules design pattern is that the participants in
286 the network can be widely distributed across very heterogeneous business ownership boundaries,
287 legal governance structures, and technical security domains. Yet, the parties need not agree to
288 conform all or most aspects of their basic roles, relationships, and activities in order to connect
289 to to systems of a trust network. Cross-domain trusted systems must, by their nature, focus
290 mandatory and enforceable rules narrowly upon the critical items that must be commonly agreed
291 in order for that network to achieve it's purpose.

292 For example, institutions participating in credit card and automated clearinghouse debit
293 transactional networks are subject to profoundly different sets of regulations, business practices,
294 economic conditions, and social expectations. The network rules focus upon the topmost agreed
295 items affecting interoperability, reciprocity, risk, and revenue allocation. The knowledge that
296 fundamental rules are subject to enforcement actions is one of the foundations of trust as well
297 as a motivation to prevent or address violations before they trigger penalties. A clear example
298 of this approach can be found with the Visa Operating Rules, covering a vast global real-time
299 network of parties that agree to rules governing their roles in the system as merchants, banks,
300 transaction processors, individual or business card holders, and other key system roles.

301 A system like this has made the interbank money transfer system among the safest systems
302 in the world and the daily backbone for exchanges of trillions of dollars, but until recently such
303 systems were only for the 'big guys'. To give individuals a similarly safe method of managing
304 personal data, the Human Dynamics research group at MIT, in partnership with the Insti-
305 tute for Data Driven Design, co-founded by John Clippinger and one author (Pentland), have
306 helped build open Personal Data Store (openPDS) [11]. See <http://openPDS.media.mit.edu>
307 for project information and <https://github.com/HumanDynamics/openPDS> for the open source
308 code.

309 The openPDS is a consumer version of a personal cloud trust network that we are now

310 testing with a variety of industry and government partners. Soon, sharing your personal data
 311 could become as safe and secure as transferring money between banks.

312 The Human Dynamics Lab has applied the system rules approach to development of in-
 313 tegrated business, technical architecture, and rules large scale institutional use of personal
 314 data stores, available as an example under MIT's creative commons license by MIT, at [https:](https://github.com/HumanDynamics/SystemRules)
 315 [//github.com/HumanDynamics/SystemRules](https://github.com/HumanDynamics/SystemRules).

316 The capacity to apply the appropriate methods of enforcement for a trust network depend
 317 upon a clear understanding and agreement among parties about the purpose of the trusted
 318 system and the respective roles or expectations of those connecting as participants. Therefor,
 319 an anchor is needed to a clear context of a Big Data operational framework and institutional
 320 controls appropriate for access and confidentiality or privacy. The following section posits the
 321 trust model and signature traits of such a context, through the lens of the New Deal on Data.

322 6 Transitioning End-User Assent Practices (Arek)

323 The way the users grant authorizations to their data is not a trivial matter. The flow of personal
 324 information, such as location data, purchases, health records can be very complex. Every tweet,
 325 every geo-tagged picture, every phone call, and every purchase with credit card, provide the
 326 user's location not only to the primary service, but also to all the applications and services that
 327 have been authorized to access and re-use these data. The authorizations may come from the
 328 end-user or, often, be granted by the collecting service, based on an umbrella terms of service,
 329 allowing the re-use of the data. Implementation of such flows was a crucial part of the Web 2.0
 330 revolution, realized with RESTful APIs, mashups, and authorization-based access. The way the
 331 personal data travel between the services has however become arguably too complex for a user
 332 to handle and manage.

333 Increasing the amount of data the user controls and granularity of this control is meaningless
 334 if it cannot be exercised in an informed way. For many years, the End User License Agreements
 335 (EULAs), long incomprehensible texts have been accepted blindly by the end-user, trusting they

336 have not agreed to anything that could harm them. The process of granting the authorizations
337 cannot be too complex, as it would prevent the user from understanding her decisions. At
338 the same time, it cannot be too simplistic, as it may not sufficiently convey the weight of the
339 privacy-related decisions. It is a challenge in itself, to build the end-user assent systems that
340 allow the user to understand and adjust their privacy settings. Complex EULAs do not promote
341 the privacy of the users, effectively pushing them to press *I Agree* in every presented window;
342 the consequences of the assent are not emphasized. The data is becoming increasingly complex
343 and our computations more sophisticated; every act of sharing can lead to great benefits to the
344 society, but also make the users very vulnerable.

345 This gap between the interface – single click – and the effect, can render the data ownership
346 meaningless; the click may wrench people and their data into systems and rules that are anti-
347 thetical to fair information practices, such as is prevalent with today's end-user licenses in cloud
348 services or applications. Managing the potentially long term and opposite dynamics fueled by
349 old deal systems operating simultaneously with the new deal systems is an important design
350 and migration challenge during the transition to a Big Data economy. During this transition
351 and after the New Deal on Data is no longer new, personal data must continue to flow in order
352 to be useful. Protecting the data of people outside of the user-controlled domain is very hard
353 without a combination of cost effective and useful business practices, legal rules, and technical
354 solutions.

355 We envision Living Informed Consent, where the user is entitled to know what data is being
356 collected about her by which entities, empowered to understand the implications of data sharing,
357 and finally put in charge of the sharing authorizations. We suggest the readers ask themselves a
358 question: *Which services know which city I am in today?*. Google? Apple? Twitter? Amazon?
359 Facebook? Flickr? This small application we have authorized a few years ago to access our
360 Facebook check-ins and forgot since then? This is an example of a fundamental question related
361 to user privacy and assent, and yet finding the answer to it may be surprisingly difficult in today's
362 ecosystem. We can hope that most of the services treat the data responsibly and according to

363 user authorizations. In the complex network of data flows however, it is relatively easy for the
 364 data to leak to services careless with it or simply malicious [7]. We need to build the solutions
 365 to help the user to make well thought-through decisions about data sharing.

366 **7 Business, Legal, and Technical Dimensions of Big Data Sys-** 367 **tems (Dazza)**

368 When it comes to data intended to be accessible over networks – whether big, personal, or other-
 369 wise – the traditional container of an institution makes less and less sense. Institutional controls
 370 apply, by definition by or to some type of institutional entity such as a business, governmental,
 371 or religious organization. A combined view of the business, legal, and technical facts and cir-
 372 cumstances surrounding big data is necessary to know what access, confidentiality, and other
 373 expectations exist. The relevant contextual aspects of Big Data of one institutional is often
 374 profoundly different from that of another. As more and more organizations use and rely upon
 375 big data, a single formula for institutional controls will not work for increasingly heterogeneous
 376 business, legal and technical environments in play.

377 Looking at an institution as a business, legal, and technical ‘system’ is one effective approach
 378 for dealing with the inherent complexity of managing heterogeneous and distributed networks of
 379 actors and interactions. The business models, interface-point operational practices and relevant
 380 assumptions must be consistent and frequently carefully agreed upon at an executive level by
 381 and with institutions as part of the value exchange involving data and access to high value,
 382 mission critical or sensitive systems and services. The applicable legal frameworks, common
 383 assumptions regarding likely allocation of liability and resolution of disputes in the event of
 384 losses, and expected types of contracting practices need to reflect and support the business
 385 goals and purposes for the system and data. When technical standards are selected, configured
 386 and applied to systems they too must support and reflect the business and legal dimensions and
 387 be supported and reflected by those dimensions.

388 Once a systems view is adopted, there is a tractable starting point to narrow or broaden
 389 the scope of view to see the smaller and larger systems and to make better and more effective
 390 use and control of big data. Within a given institution, there may in fact be many different
 391 discernable institutions and corresponding systems and any given system of one institution will
 392 frequently in fact exist across many different discernable institutions. However, defining as a
 393 ‘system’ the thing to which institutional controls apply provides an achievable and measurable
 394 basis for balancing privacy, access and other interests in big data. **AS: The paragraph above**
 395 **is hard to understand I think.**

396 Many organizations are structured with clear leadership on business, legal, and technical
 397 issues functionally assigned to top level executive roles. Business issues are typically allocated
 398 to roles such as CEO, COO or CFO, while leadership on legal issues is commonly assigned to
 399 roles like general counsel and regulatory compliance and technical leads are often the roles of
 400 CIO, CTO or CSO. Having top level leadership for each of the business, legal, and technical
 401 aspects of a trust network is a critical success factor.

402 8 Big Data and Personal Data Institutional Controls (Thomas)

403 The phrase “institutional controls” refers to safeguards and protections by use of legal, policy,
 404 governance, and other non-strictly technical, engineering, or mechanical measures. The phrase
 405 institutional controls in a Big Data context can perhaps best be understood by examining how
 406 the concept has been applied to other domains. The most prevalent use of institutional controls
 407 has been in the field of environmental regulatory frameworks.

408 A good example of how this concept supports and reflects the goals and objectives of en-
 409 vironmental regulation can be found in the policy documents of the Environmental Protection
 410 Agency (EPA). This following definition is instructive, and is part of the Institutional Control
 411 Glossary of Terms [38]:

412 “Institutional Controls - Non-engineering measures intended to affect human activi-

413 ties in such a way as to prevent or reduce exposure to hazardous substances. They
414 are almost always used in conjunction with, or as a supplement to, other measures
415 such as waste treatment or containment. There are four categories of institutional
416 controls: governmental controls; proprietary controls; enforcement tools; and infor-
417 mational devices.”

418 Going deeper, the article by DeMeo and Doar [12] defines institutional controls thusly:

419 “Institutional controls are administrative and legal controls that help minimize the
420 potential for human exposure to contamination and/or protect the integrity of the
421 physical remedy. They can include recorded restrictive covenants, but land use
422 laws and regulations, deed restrictions, department consent orders, and conservation
423 easements are all institutional controls.”

424 In domains of information technology, this approach is most commonly reflected as “enter-
425 prise controls” related to security. See, for example, the report [20] stating: “Enterprise mobility
426 technologies, especially those designed to retrofit enterprise controls on top of consumer mobile
427 devices, are rapidly evolving. This was a message we heard loud and clear in the study.” This
428 study and analysis also reveals much about the internal controls needed to accommodate mobile
429 device use by employees. In both capacities as employee, consumer, and other roles, the use of
430 mobile devices triggers myriad legal, policy, and other implications for institutional controls.

431 In the legal domain, this concept frequently emerges under the moniker “regulatory compli-
432 ance” or “legal compliance” anchored in legal and regulatory frameworks such as Health Insur-
433 ance Portability and Accountability Act (HIPAA) and Sarbanes-Oxley (SOX). These statutory
434 legal frameworks require covered organizations to established integrated sets of governance,
435 legal, transactional, security, and other internal controls to avoid violating the rules. The in-
436 stitutional controls are accomplished in tight integration with engineering and other measures
437 in order to ensure compliance and to control legal and security risk. The use of institutional
438 controls of this type are fundamental methods for achieving and maintaining the transition to a

439 digital, networked, and Big Data footing for any private company, government agency, or other
440 organization.

441 Consider again the analogy of institutional controls in the context of environmental law, and
442 how these types of measures can be applied in the Big Data, privacy, and access context to digital
443 environments. Given the relatively mature and stable state of environmental regulation, there is
444 much to be learned by examining this context of institutional controls. Environmental regulatory
445 compliance with waste management cleanup requirements could include institutional controls
446 restricting land use on adjacent property. In these situations, it is possible that the remediation
447 strategy requires significant use of land outside the property boundaries of the cleanup site.
448 In these cases, the regulators and the land owner responsible for the regulated property must
449 find ways to ensure a common approach among multiple owners and across multiple property
450 environments. Use of measures such as a clauses on the relevant deeds, an enforceable consent
451 order, or regulations and zoning rules are examples of more severe institutional controls that
452 can be employed to ensure consistent and effective actions are taken across ownership and real
453 property boundaries.

454 See, for example, Florida Department of Environmental Protection (FDEP), Division of
455 Waste Management [15] which states that “...RMO III does contemplate contamination beyond
456 the Property boundaries, which would require agreement by the adjacent owners to put an RC
457 on their properties as well.”

458 The concept of an “institutional control boundary” is especially clarifying and powerful when
459 applied to the networked and digital boundaries of an institution. In the context of Florida’s
460 environmental regulation frameworks, the phrase is applied to describe the various types of
461 combinations risk management levels related to target cleanup standards and extend beyond
462 the area of a physical property boundary. Also see a recent University of Florida report on
463 Development of Cleanup Target Levels (CTLs) [8] stating “Risk Management Options Level
464 III, like Level II, allows concentrations above the default groundwater CTLs to remain on site.
465 However, in some rare situations, the institutional control boundary at which default CTLs must

466 be met can extend beyond the site property boundary.”

467 The EPA provides considerable information on the nature and use of institutional controls,
 468 including situations when the situational scope extends to adjacent properties owned by third
 469 parties. See, generally, *EPA Hazardous Waste Corrective Action Guidance on Institutional Con-*
 470 *trols* [38]. Also see: *Institutional Controls Bibliography: Institutional Control, Remedy Selection,*
 471 *and Post-Construction Completion Guidance and Policy, December 2005* [37].

472 When institutional controls would apply to “separately owned neighboring properties” a
 473 number of issues arise. Engagement with affected third parties, requiring the party responsible
 474 for site cleanup to use “best efforts” to attain agreement by third parties to institute the relevant
 475 institutional controls, use of third party neutrals to resolve disagreements regarding the appli-
 476 cation with institutional control,s or forcing an acquisition of the neighboring land by forcing
 477 the party responsible to purchase the property of by purchase of the property directly by the
 478 EPA [39].

479 In the context of Big Data, privacy, and access, institutional controls are seldom, if ever,
 480 the result of government regulatory frameworks such as are seen in the environmental waste
 481 management oversight by the EPA. Rather, institutions applying measures constituting institu-
 482 tional controls in the big data and related information technology and enterprise architecture
 483 contexts will typically employ governance safeguards, business practices, legal contracts, techni-
 484 cal security, reporting, and audit programs and a various risk management measures. Inevitably,
 485 institutional controls for Big Data will have to operate effectively across institutional boundaries,
 486 just as environmental waste management internal controls must sometimes be applied across real
 487 property boundaries and may subject multiple different owners to enforcement actions corre-
 488 sponding to the applicable controls. Short of government regulation, the use of system rules as a
 489 general model are one widely understood, accepted, and efficient method for defining, agreeing,
 490 and enforcing institutional and other controls across business, legal, and technical domains of
 491 ownership, governance, and operation.

492 The use of system rules and integrated participation agreements by developers and end-

users is a way to ensure intended operational frameworks conform to applicable institutional controls. The example of Living Informed Consent described in this chapter, demonstrates how institutional controls comprised of legal and definite workflow measures, in concert with technical methods, can result in a higher level of performance, while appropriately balancing legitimate interests of various parties regarding use and access to personal data.

Following the World Economic Forum recommendations of treating personal data stores in the manner of bank accounts [41], there are a number of infrastructure improvements that need to be realized, if the personal data ecosystem is to flourish and deliver new economic opportunities. We believe the following infrastructure improvements are necessary for the coming personal data ecosystem: **AS: We should remove the bullets, turn them into continuous text.**

- *New global data provenance network:* In order for personal data to be treated like bank accounts, the origin information regarding data items coming into the data store must be maintained [19]. In other words, the provenance of all data items must be accounted for by the IT infrastructure upon which the personal data store operates. The heterogeneous provenance databases must then be interconnected in order to provide a resilient and scalable platform for audit and accounting systems to track and reconcile the movement of personal data from the respective data stores.
- *Trust network for computational law:* In order for trust to be established between parties who wish to exchange personal data, we foresee that some degree of “computational law” technologies may have to be integrated into the design of personal data systems. Such technologies should not only verify terms of contracts (e.g. terms of data use) against user-defined policies but also have mechanisms built-in to ensure non-repudiation of entities who have accepted these digital contracts. Efforts such as [1, 2] are beginning to bring non-repudiation and enforceability of contracts into the technical protocol flows.
- *Development of institutional controls for digital institutions:* Currently there are a number of proposal for the creation of virtual currencies (e.g. BitCoin [5], Ven [34]) in which the

519 systems have the potential to evolve into self-governing “digital institutions” [18]. Such
 520 systems and institutions that operate on them will necessitate the development of a new
 521 paradigm to understand the aspects of institutional control within their context.

522 9 Scenarios of Use in Context (Dazza)

523 Supporting the effective development of institutional controls for big data requires an under-
 524 standing of how to define and work with the applicable context surrounding the scenarios within
 525 which the Big Data exists. In particular, the New Deal on Data will require a set of Institu-
 526 tional Controls involving governance, business, legal, and technical aspects that are knowable
 527 only with reference to the relevant context of a factually based scenario of use. The following
 528 scenarios demonstrate signature features of the New Deal on Data in various contexts and serve
 529 as an anchor to evaluate what Institutional Controls are well aligned.

530 9.1 Example Scenario: Research Systems

531 **AS: This entire section requires significant write-through.**

532 Computational Social Science (CSS) studies are based on data collected often with an ex-
 533 tremely high resolution and scale [22]. Using computational power combined with mathematical
 534 models, such data can be used to provide insights into human nature. Much of the data collected,
 535 for example mobility traces are sensitive and private; most individuals would feel uncomfortable
 536 sharing them publicly. The need for solutions to ensure the privacy of the individuals has grown
 537 alongside the data collection efforts.

538 The data collection in the CSS context is based on the informed consent of the partici-
 539 pants. Countries have different bodies regulating such studies, for example Institutional Research
 540 Boards (IRBs) in the US. Although certain minimal requirements for implementing informed
 541 consent exist**AS: reference** , they are often not very well suited for the large-scale studies,
 542 where the amount and sensitivity of the data calls for sophisticated privacy controls. As the
 543 scale of the studies grows, in terms of the number of participants, collected bits per user, and

544 duration, the EULA-style informed consent is no longer sufficient and makes it hard to claim
545 that participants in fact expressed informed consent.

546 One author (Stopczynski) deployed this year a 1,000 phones study at Technical University
547 of Denmark, freshmen students received mobile phones in order to study their networks and
548 social behavior in the important change moment of their lives, when joining the university.
549 The study, called SensibleDTU (<https://www.sensible.dtu.dk/?lang=en>), uses not only data
550 collected from the mobile phones (location, Bluetooth-based proximity, call and sms logs etc.)
551 but also data collected from social networks, questionnaires filled out by participants, behavior
552 in economic games and so on. As the data is collected in the context of the university, there is
553 potentially a big issue of students feeling obliged to participate in the study, feeling that their
554 grades may depend on it, or that the data may influence their grades. In this context, we see
555 the implementation of Living Informed Consent not only as a technical mean to put participants
556 in control of the data we collect, but also to convey the message about the opt-in nature of the
557 study, the boundaries of the data usage, and parties accessing the data.

558 It is not feasible to explain the terms and answer all the questions to all 1,000 students
559 personally. The controls must be self-explanatory as much as possible, and guide the user from
560 the first opening of the link to the study to the grant of the authorizations. At the same time,
561 every click made by the user, should be an expression of an informed decision, so the user journey
562 must be a balance of guidance and understanding. For this reason we have created a set of web
563 applications, allowing the users to enroll into the study, express informed consent, and interact
564 with their data.

565 As the study will last for several years, hopefully allowing us to see the life of a student from
566 the very first friendships made until the graduation party, the consent must remain alive. It is
567 again a matter of balance: we do not want the participants to feel under constant surveillance
568 (as they are not, the data is used mostly in aggregated form), at the same time to remember that
569 in fact, the data is being collected and used. We are still trying to understand how to achieve
570 this equilibrium: how often should we remind the users about the collection effort? should they

571 re-authorize applications from time to time? We see a great hope in the applications we create
572 for the users to provide certain services, simple such as life-logging where they can see how
573 active they are, what are their top places etc. and more advanced, such as artistic visualizations
574 of their social networks. Making the user aware of the data by transforming them into value,
575 can greatly benefit the privacy, making users constantly aware what is being collected, but also
576 what kind of value they can get out of it.

577 When a study of such scale is deployed, the particular experiments and sub-studies may
578 not be exactly defined from the very beginning. The initial deployment is a creation of a
579 testbed, where shorter or longer experiments can take place; for example part of the population
580 may participate in the experiment of quantifying the impact of feedback application on their
581 activity levels. Being able to create such experiments in an efficient way is a huge value for the
582 researchers. To do that in the most frictionless way, we give the users the choice to opt-in to
583 those additional experiments, providing some financial or other benefits. This is only possible
584 if there is a notion of identity of the participants, stronger and more useful than a piece of
585 paper with a signature. This identity allows us to reach out to people, offer them additional
586 experiments, and let them agree or disagree to them.

587 This touches upon the re-usability of data, as the new experiments may require additional
588 data to be collected, but also have access to all the existing data, based on user authorization.
589 We can imagine going even further, where entirely different studies can re-use participants data
590 from a previous study based on their authorization. When the data are owned by the users,
591 they are free to authorize access to them to any party that requests it. We can see a New Deal on
592 Data pattern here: rather than services (studies) talking to each other about the user data, they
593 talk directly to the users, seeking their authorization. This can address a very important problem
594 in the research context, the data re-use in a privacy-aware manner. Rather than publishing a
595 static dataset, where the users have lost control over their data, live and fresh data can be
596 continuously accessed by any study that the user agrees to be a part of.

597 Many studies will be willing to offer money or other value for the access to the data. Other

will provide the user the opportunity to have new data collected. This way, the data collection becomes an opportunity for the user to enrich their personal dataset, and to benefit from it in the future. Join our study and we will provide you with a smartphone and collect your movement patterns for a year; we will do science and you will gain new data that can get you better value or deals in different services. You may now be eligible for a different study. Or your music recommendation may get better, because your music service can make a use of this extra data. Your data.

9.2 Scenarios of Use Today, Tomorrow and the Day After

AS: This paragraph is impossible to follow for someone without deep background knowledge of what is the message. Too many random made up scenarios, entities, all mashed together.

By inquiring into and noting the four facets of relevant context described above, it is possible to describe the basic material contours of any scenario within which Big Data exists such that the operational framework and adequate approaches to access, use, confidentiality, and other key interests can be sustainably balanced. In a commercial scenario the relevant people might be a consumer, merchants, banks, products manufacturers, third party app developers, and individual members of that consumers bowling team. The relevant transactions might be a purchase of goods by the consumer from the merchant and the corresponding app that was embedded in the goods and the downstream transaction of involving the consumer now transacting with the merchant bowling alley and interacting with a bowling team, with whom activity and sports performance data are shared and aggregated and further mashed up. The rest of the context can be described for any given scenario and this all could be expressed specifically rather than by role simply by running a report from the system to indicate it was in fact John Doe, of openpds.org/owner/571 purchasing a smart bowling ball from Bowl-a-Tronic of bowlapp-good.com/store/221 and so on for each party that played a role in the relevant scenario. The same techniques, used for scenarios in other economic sectors and social endeavors shed light

on the fundamental nature and implications of Big Data and options for the use of operational frameworks acting across domains to balance privacy and access, among other interests.

AS: Bold claims here, not sure if we have sufficient support for them in the chapter.

This book represents a high value opportunity to take stock of the current state and dominant trends related to Big Data and help to illuminate important choices at a moment of early adoption, dynamic innovation, and wide open possibilities. By contemplating the relevant contexts of today's scenarios of use in, say, the fields of education, entertainment, government, manufacturing, transportation, and many other core anchors of human activity, we have traction to postulate how today's prevailing trends are likely to result and what changes - perhaps quite small but of profound long term impact - could lead to materially different better outcomes. Consider that if the essence of the New Deal on Data was accepted today, or soon, the nature, tenor, capabilities, and experience of living by future generations could be unrecognizably better. Simply extrapolate from the current anomalous practices regarding personal data and individual identity and push forward the timeline by 5, 10, 20 years and beyond. The current trajectory ends up with dystopian scenarios that effectively reverse hard fought, but easily lost constitutional deal of the United States and social compact of common law societies.

By contrast, by adopting the New Deal on Data now it is possible to set conditions that promote prosperity and invention even before the New Deal on Data frameworks are formally launched. This is because the uncertainty and confusion about the basic premises and expectations around personal data and identity will be resolved and so investment and risk taking on a firm foundation can be unleashed. The value of Big Data can be accessed at less direct cost and lower risk when uncertainties about privacy liability are addressed and significant the new value is created by enabling wide scale permission based access to personal data and computations about such data. Adopting use of personal data services in phases, such one economic sector, transaction type or data type at a time enables access to the lower costs and new value in a reasonable manner that allows for time to prepare for and stage each phase of adoption.

By staging and phasing the New Deal on Data typical objections to change based on grounds of cost, disruption or over regulation can be addressed. Policy incentives can further address these objections, such as allowing safe harbor protections for conduct of organizations operating under the rules of a trust network. Policy makers can resolve other difficulties by combinations of strategic transition management methods like allowing safe harbor compliance delays, or approving alternative adoption paths and granting other non-substantive waivers to ease any burdens of migrating to new business methods. The key point is change management can be designed to achieve enough value at every phase for every key stakeholder group such that self interests and the broader interests are all aligned with the public good.

10 Future Research (Brian)

Our traditional methods of testing and improving government, organizations, and so on are of limited use in building a data-driven society. Even the scientific method that we normally use do not work as well as we might expect, because there are so many potential connections that our standard statistical tools generate less than useful results.

The reason is that with such rich data, you can easily uncover misleading or unactionable correlations. For instance, let us imagine we discover that people who are unusually active are more likely to get the flu. This is a real example: when we examined the minute-by-minute behavior of a small university community - a real-time flow of gigabytes per day for an entire year - we noticed that an unusual level of running around often predicted onset of the flu [24]. But if we can only analyze the data using traditional statistical methods, we have the problem of discerning why this is true. Is it because the flu virus makes us more active in order to spread itself more quickly? While it is more likely that interacting with many more people than usual makes you more likely to catch the flu, you can't be sure that this is the true cause based on the real-time stream of data alone.

Normal analysis methods do not suffice to answer this type questions, because we do not know all the possible alternatives, and so we cannot form a limited, testable number of clear

677 hypotheses. Instead, we need to devise new ways to test the causality of connections in the real
 678 world. We can no longer rely on laboratory experiments; we need to do the experiments in the
 679 real world, typically on massive, real-time streams of data.

680 10.1 Research on Design and Deployment of Big Data Systems

681 **AS: I do not understand this paragraph? What is top current research? Where is it**
 682 **applied?** In order to achieve low risk, high value outcomes efficiently, design and deployment
 683 of the coming global wave of Big Data systems should apply top current research. To understand
 684 and address the unique problems and prospects associated with big personal data, the relevant
 685 context must be identified and corresponding rules-driven capabilities must be designed into the
 686 underlying systems.

687 People or systems can determine the right rules to apply to data when the right information
 688 is reliably attached to or logically associated with that data in a standard manner **AS: I think I**
 689 **understand this previous sentences but I' m not sure. What is 'a standard manner'**
 690 **here? What is the right information? It seems it is described in the next sentences,**
 691 **maybe remove this one then?** . Any system that can make, use, receive, or share Big Data
 692 must be capable of associating provenance and purpose for all data in a common and actionable
 693 manner. Requiring a lot of narrative documentation and background about the nuances and
 694 circumstances surrounding every data set is both impractical and counterproductive. By con-
 695 trast, a small amount of metadata listing or reliably linking the parties, transactions, systems
 696 and provenance of the data would suffice. This relevant context together with the data forms
 697 the basis for accountable analysis on big personal data.

698 It is important for science and research to develop further solutions and options ensuring
 699 contextually appropriate rules can be applied by big data systems. For rules to be effectively
 700 applied, systems must not only be able to establish which rules apply but also support the right
 701 functional capabilities and have appropriate information structure, format, and meta-data.

702 Some capabilities will likely be essential to all Big Data systems, such as highly scalable

active storage, standard methods for integration with other Big Data systems, and a processing architecture enabling high speed statistical analytics. But there are and will continue to emerge multiple types of Big Data systems. Some functions or controls will likely be important – or even feasible – only for certain types of future systems. For instance, it is reasonable to expect some systems will specialize in enormous volumes of entirely non-personal data from many real-time sources (e.g. for soil science, materials engineering, astronomy) while other Big Data systems will hinge upon mass quantities of highly sensitive personal information (e.g. for clinical medicine, education and life-long learning, social entertainment).

AS: I feel Big Data term is abused in this section...

While some capabilities, such as ingesting and processing astronomical data-sets, will be unique to only a subset of Big Data systems, it is reasonable to anticipate that data will be increasingly cross-tabulated, merged, and otherwise shared with other systems and data. It can be nearly impossible to conclusively predict for the entire life of a system what data will be received by, created in, or transmitted from that system at the design phase. This prediction is all the harder to make when the systems are intended for Big Data.

The four contextual facets of people, interactions, technology, and data provide a sound underpinning for the design of new Big Data and Web 2.0 systems. The existing systems design and development processes of establishing business cases, use cases, agile stories, functional requirements, etc. do not reliably identify the factors most relevant to use of Big Data, especially in a Web 2.0 massively distributed environment. The four facets can also be used to analyze appropriate, required or prohibited uses for existing Big Data systems. However, it can be difficult to extract the relevant information from or apply any effective control on systems used for Big Data but designed to achieve limited purposes in hierarchical closed environments.

Big Data, by its nature, represents a new set of business, legal, and technical capabilities and requirements. Most of the worlds systems today are not capable of ingesting, storing, using, or dynamically flowing big data with other systems. Considering that a) Big Data is of high value immediately and higher value in the short and long terms, and b) the young but competitive

730 marketplace of Big Data system components, platforms, applications, and other solutions is a
 731 hotbed of innovation it can be predicted that a transition to Big Data systems will continue.
 732 The key observation is that virtually all Big Data systems have yet to be designed, implemented,
 733 customized, or deployed. Institutions that are the current early adopters of today's Big Data
 734 system will soon replace those systems and the rest of the world will adopt big data systems in
 735 phases over time. Based upon this observation, **AS: ??????????????**

736 10.2 Research on Big Data for Design of Institutions

737 Using massive, live data to design institutions and policies is outside of our normal way of
 738 managing things. We live in an era that builds on centuries of science and engineering, and
 739 the standard choices for improving systems, governments, organizations, and so on are fairly
 740 well understood. Therefore our scientific experiments normally need only consider a few clear
 741 alternatives, 'plausible hypotheses'.

742 With the coming of Big Data, we are going to be operating very much out of our old,
 743 familiar ballpark. These data are often indirect and noisy, and so interpretation of the data
 744 requires greater care than usual. Even more importantly, a great deal of the data is about
 745 human behavior, and the questions are ones that seek to connect physical conditions to social
 746 outcomes. Until we have a solid, well-proven, and quantitative theory of social physics, we will
 747 not be able to formulate and test hypotheses in the way we can when we design bridges or
 748 develop new drugs.

749 Therefore, we must move beyond the closed, laboratory-based question-and-answering pro-
 750 cess that we currently use, and begin to manage our society in a new way. We must begin to test
 751 connections in the real world far earlier and more frequently than we have ever had to do before,
 752 using the methods the Human Dynamics research group have developed with our collaborators
 753 for the Friends and Family [3] or the SensibleDTU (<https://www.sensible.dtu.dk>) study. We
 754 need to construct Living Laboratories – communities willing to try a new way of doing things or,
 755 to put it bluntly, to be guinea pigs – in order to test and prove our ideas. This is new territory

756 and so it is important for us to constantly try out new ideas in the real world in order to see
757 what works and what does not.

758 An example of such a Living Lab is the ‘open data city just launched by one author (Pentland)
759 with the city of Trento in Italy, along with Telecom Italia, Telefonica, the research university
760 Fondazione Bruno Kessler, the Institute for Data Driven Design, and local companies. Import-
761 tantly, this Living Lab has the approval and informed consent of all its participants they know
762 that they are part of a gigantic experiment whose goal is to invent a better way of living. More
763 detail on this Living Lab can be found at <http://www.mobileterritoriallab.eu/>.

764 The goal of this Living Lab is to develop new ways of sharing data to promote greater civic
765 engagement and exploration. One specific goal is to build upon and test trust-network software
766 such as our openPDS system. Tools such as openPDS make it safe for individuals to share
767 personal data (e.g., health data, facts about your children) by controlling where your data go
768 and what is done with them.

769 The specific research questions we are exploring depend upon a set of “personal data ser-
770 vices” designed to enable users to collect, store, manage, disclose, share, and use data about
771 themselves. These data can be used for the personal self-empowerment of each member, or
772 (when aggregated) for the improvement of the community through data commons that enable
773 social network incentives. The ability to share data safely should enable better idea flow among
774 individuals, companies, and government, and we want to see if these tools can in fact increase
775 productivity and creative output at the scale of an entire city.

776 An example of an application enabled by the openPDS trust frame work is sharing of best
777 practices among families with young children. How do other families spend their money? How
778 much do they get out and socialize? Which preschools or doctors do people stay with for the
779 longest time? Once the individual gives permission, our openPDS system allows such personal
780 data to be collected, anonymized, and shared with other young families safely and automatically.

781 The openPDS system lets the community of young families learn from each other without
782 the work of entering data by hand or the risk of sharing through current social media. While

783 the Trento experiment is still in its early days, the initial reaction from participating families is
784 that these sorts of data sharing capabilities are valuable, and they feel safe sharing their data
785 using the openPDS system.

786 The Trento Living Lab will let us investigate how to deal with the sensitivities of collecting
787 and using deeply personal data in real-world situations. In particular, the Lab will be used as a
788 pilot for the New Deal on Data and for new ways to give users control of the use of their personal
789 data. For example, we will explore different techniques and methodologies to protect the users
790 privacy while at the same time being able to use these personal data to generate a useful data
791 commons. We will also explore different user interfaces for privacy settings, for configuring the
792 data collected, for the data disclosed to applications and for those shared with other users, all
793 in the context of a trust framework.

794 11 Conclusions

795 Our societies today face unprecedented challenges. Solving those problems will require access
796 to the personal data, so we can understand how the society works, how we move around, what
797 makes us productive, how the ideas and diseases spread. The insights must be actionable,
798 available in real-time, and engaging the population, creating the nervous system of the society.
799 In this chapter we have reviewed how Big Data collected in institutional context can be used for
800 the public good. In many cases, the data needed for creating better society is already collected
801 and exists closed in silos of companies and governments. Using well designed and implemented
802 set of institutional controls, covering business, legal, and technical dimensions, we described how
803 the silos can be opened. The framework for doing this – the New Deal on Data – postulates that
804 the primary driver of the change must be the ownership of the personal data, given to people
805 about whom the data is. This ownership, the right to use, transfer, and remove the data ensures
806 that the data is available for public good, while at the same time protecting the privacy of the
807 citizens.

808 The New Deal on Data is still new. Here we described our efforts in understanding the

technical means of how it can be implemented, the legal framework around it, business ramifications, and the direct value that can be derived from researchers, companies, governments, and users having more access to the data. It is clear that companies must play the major role in the implementation of the New Deal, incentivized by business opportunities and pressured by the legislation and demand of the users. Only with such orchestration it will be possible to change the current feudal system of the data ownership and finally put the immense quantities of the collected personal data to good use.

References

1. Binding obligations on User-Managed Access (UMA) participants. Technical Specifications draft-maler-oauth-umatrust-01, Kantara Initiative, July 2013.
2. User-Managed Access (UMA) profile of OAuth2.0. Technical Specifications draft-hardjono-oauth-umacore-08, Kantara Initiative, December 2013.
3. Nadav Aharony, Wei Pan, Cory Ip, Inas Khayal, and Alex Pentland. Social fmri: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing*, 7(6):643–659, 2011.
4. Sinan Aral and Dylan Walker. Identifying influential and susceptible members of social networks. *Science*, 337(6092):337–341, 2012.
5. Simon Barber, Xavier Boyen, Elaine Shi, and Ersin Uzun. Bitter to Better – how to make Bitcoin a better currency. In *Proceedings Financial Cryptography and Data Security Conference (Lecture Notes in Computer Science Volume 7397)*, pages 399–414, April 2012.
6. Ellen Barry. Protests in moldova explode, with help of twitter. *New York Times*, 8, 2009.
7. Nick Bilton. Girls around me: An app takes creepy to a new level. *The New York Times*.

- 831 8. Center for Environmental & Human Toxicology University of Florida. Development of
 832 Cleanup Target Levels (CTLs) For Chapter 62-777, F.A.C. Technical report, Division of
 833 Waste Management Florida Department of Environmental Protection, February 2005.
- 834 9. Paul Lukowicz Bert Arnrich Cornelia Setz Gerhard Troster David Tacconi, Oscar Mayora
 835 and Christian Haring. Activity and emotion recognition to support early diagnosis of
 836 psychiatric diseases. pages 100–102. IEEE, 2008.
- 837 10. Yves-Alexandre de Montjoye, César A Hidalgo, Michel Verleysen, and Vincent D Blondel.
 838 Unique in the crowd: The privacy bounds of human mobility. *Scientific reports*, 3, 2013.
- 839 11. Yves-Alexandre de Montjoye, Samuel S Wang, Alex Pentland, Dinh Tien Tuan Anh, An-
 840 witaman Datta, Kevin W Hamlen, Lalana Kagal, Murat Kantarcioglu, Vaibhav Khadilkar,
 841 Kerim Yasin Oktay, et al. On the trusted use of large-scale personal data. *IEEE Data*
 842 *Eng. Bull.*, 35(4):5–8, 2012.
- 843 12. Ralph A. DeMeo and Sarah Meyer Doar. Restrictive covenants as institutional controls
 844 for remediated sites: Worth the effort? *The Florida Bar Journal*, 85(2), 2011.
- 845 13. Nathan Eagle and Alex Pentland. Reality mining: sensing complex social systems. *Per-*
 846 *sonal and ubiquitous computing*, 10(4):255–268, 2006.
- 847 14. Jonathan Woetzel et al. Preparing for china’s urban billion. 2009.
- 848 15. Florida Department of Environmental Protection - Division of Waste Management. Insti-
 849 tutional Controls Procedures Guidance. [http://www.dep.state.fl.us/waste/quick\](http://www.dep.state.fl.us/waste/quick_topics/publications/wc/csf/icpg.pdf)
 850 [_topics/publications/wc/csf/icpg.pdf](http://www.dep.state.fl.us/waste/quick_topics/publications/wc/csf/icpg.pdf), June 2012.
- 851 16. Kate Greene. Reality mining. *Technology Review*, 2008.
- 852 17. Lev Grossman. Iran protests: Twitter, the medium of the movement. *Time Magazine*,
 853 17, 2009.

- 854 18. Thomas Hardjono, Patrick Deegan, and John Clippinger. On the Design of Trustworthy
855 Compute Frameworks for Self-Organizing Digital Institutions. In *Proceedings of the 16th*
856 *International Conference on Human-Computer Interaction*, 2014.
- 857 19. Thomas Hardjono, Daniel Greenwood, and Alex Pentland. Towards a trustworthy digital
858 infrastructure for core identities and personal data stores. In *Proceedings of the ID360*
859 *Conference on Identity*. University of Texas, April 2013.
- 860 20. Juniper Networks. Secure Data Access Anywhere and Anytime: Current Landscape and
861 Future Outlook of Enterprise Mobile Security. A forrester consulting thought leadership
862 paper commissioned by att and juniper networks, Forrester Research, October 2012.
- 863 21. Meglena Kuneva. Roundtable on Online Data Collection, Targeting and Profiling . [http:](http://europa.eu/rapid/press-release_SPEECH-09-156_en.htm)
864 [//europa.eu/rapid/press-release_SPEECH-09-156_en.htm](http://europa.eu/rapid/press-release_SPEECH-09-156_en.htm), 2009.
- 865 22. David Lazer, Alex Sandy Pentland, Lada Adamic, Sinan Aral, Albert Laszlo Barabasi,
866 Devon Brewer, Nicholas Christakis, Noshir Contractor, James Fowler, Myron Gutmann,
867 et al. Life in the network: the coming age of computational social science. *Science (New*
868 *York, NY)*, 323(5915):721, 2009.
- 869 23. Antonio Lima, Manlio De Domenico, Veljko Pejovic, and Mirco Musolesi. Exploiting
870 cellular data for disease containment and information campaigns strategies in country-
871 wide epidemics. School of computer science university of birmingham technical report
872 csr-13-01, University of Birmingham, May 2013.
- 873 24. Anmol Madan, Manuel Cebrian, David Lazer, and Alex Pentland. Social sensing for
874 epidemiological behavior change. In *Proceedings of the 12th ACM international conference*
875 *on Ubiquitous computing*, pages 291–300. ACM, 2010.
- 876 25. AC Madrigal. Dark social: We have the whole history of the web wrong. *The Atlantic*,
877 2013.

- 878 26. Alan Mislove, Sune Lehmann, Yong-Yeol Ahn, Jukka-Pekka Onnela, and J Niels Rosen-
879 quist. Pulse of the nation: Us mood throughout the day inferred from twitter. *Accessed*
880 *November, 22(2011):2011*, 2010.
- 881 27. Arvind Narayanan and Vitaly Shmatikov. Robust de-anonymization of large sparse
882 datasets. In *Security and Privacy, 2008. SP 2008. IEEE Symposium on*, pages 111–125.
883 IEEE, 2008.
- 884 28. Wei Pan, Yaniv Altshuler, and Alex Sandy Pentland. Decoding social influence and
885 the wisdom of the crowd in financial trading network. In *Privacy, Security, Risk and*
886 *Trust (PASSAT), 2012 International Conference on and 2012 International Conferenece*
887 *on Social Computing (SocialCom)*, pages 203–209. IEEE, 2012.
- 888 29. Wei Pan, Gourab Ghoshal, Coco Krumme, Manuel Cebrian, and Alex Pentland. Urban
889 characteristics attributable to density-driven tie formation. *Nature communications*, 4,
890 2013.
- 891 30. ALEX PENTLAND. Reality mining of mobile communications: Toward a new deal on
892 data. *The Global Information Technology Report 2008–2009*, page 1981, 2009.
- 893 31. Alex Pentland, David Lazer, Devon Brewer, and Tracy Heibeck. Using reality mining to
894 improve public health and medicine. *Stud Health Technol Inform*, 149:93–102, 2009.
- 895 32. Vivek K Singh, Laura Freeman, Bruno Lepri, and Alex Sandy Pentland. Classifying
896 spending behavior using socio-mobile data. *HUMAN*, 2(2):pp–99, 2013.
- 897 33. Chaoming Song, Zehui Qu, Nicholas Blumm, and Albert-László Barabási. Limits of
898 predictability in human mobility. *Science*, 327(5968):1018–1021, 2010.
- 899 34. Stan Stalnaker. The Ven currency, 2013. <http://www.ven.vc>.
- 900 35. Latanya Sweeney. Simple demographics often identify people uniquely. *Health (San Fran-*
901 *cisco)*, pages 1–34, 2000.

- 902 36. The White House. National Strategy for Trusted Identities in Cyberspace: Enhancing On-
903 line Choice, Efficiency, Security, and Privacy. The White House, April 2011. Available on
904 http://www.whitehouse.gov/sites/default/files/rss_viewer/NSTICstrategy_041511.pdf.
- 905 37. United States Environmental Protection Agency. Institutional Controls Bibliography.
906 <http://www.epa.gov/superfund/policy/ic/guide/biblio.pdf>, December 2005.
- 907 38. United States Environmental Protection Agency. RCRA Corrective Action Institu-
908 tional Controls - glossary. [http://www.epa.gov/epawaste/hazard/correctiveaction/](http://www.epa.gov/epawaste/hazard/correctiveaction/resources/guidance/ics/glossary1.pdf)
909 [resources/guidance/ics/glossary1.pdf](http://www.epa.gov/epawaste/hazard/correctiveaction/resources/guidance/ics/glossary1.pdf), 2007.
- 910 39. United States Environmental Protection Agency. Institutional Controls: A Guide to Plan-
911 ning, Implementing, Maintaining, and Enforcing Institutional Controls at Contaminated
912 Sites. Technical Report OSWER 9355.0-89 EPA-540-R-09-001, EPA, December 2012.
- 913 40. Jessica Vitak, Paul Zube, Andrew Smock, Caleb T Carr, Nicole Ellison, and Cliff Lampe.
914 It's complicated: Facebook users' political participation in the 2008 election. *CyberPsy-*
915 *chology, behavior, and social networking*, 14(3):107–114, 2011.
- 916 41. World Economic Forum. Personal Data: The Emergence of a New
917 Asset Class, 2011. Available on [http://www.weforum.org/reports/](http://www.weforum.org/reports/personal-data-emergence-new-asset-class)
918 [personal-data-emergence-new-asset-class](http://www.weforum.org/reports/personal-data-emergence-new-asset-class).