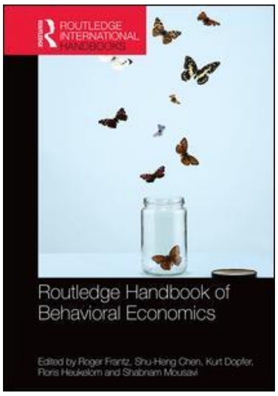

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SMART SOCIETIES

Shu-Heng Chen, Bin-Tzong Chie, and Chung-Ching Tai

Introduction

In their 1995 article entitled "Quantitative and Computational Innovation in Investment Management," Leinweber and Arnott (1995) raised two questions: "If you had unlimited computational power, what would you do with it?" and "What would you do differently if you were completely unconstrained by the capacity of your computers?" By slightly rephrasing these two questions, we immediately see a "digital" version of these two questions: "If you could *digitize everything*, what would you do with it?" and "What would you do *differently* if you were completely unconstrained by *the capacity of your digitalization*?"

The motivation to write this chapter from the perspective of behavioral economics is driven by the prevalence of digital societies in various forms, such as digital democracy, digital governance, digital media, and digitalization of the protocols, routines, and archives by which modern society is now defined, shaped, and operated. However, a digital society is not "automatically" equivalent to a smart society; in fact, a number of studies indicate exactly the worrying trend that digitalization can contribute to the dumbness, shallowness and instability of that society (Keen, 2007; Bauerlein, 2008).[1] Despite this shadow, the fundamental question that concerns behavioral economists is: To what extent can digitalization enhance our decision making and choice quality? Hence, we need to ask how the digitalization process changes human behavior or decision rules such that it may be easier to shape a smart society and a good society. Furthermore, from the viewpoint of the behavioral foundations of public policies, we are interested in knowing how the digitalization process can be used in the vein of *nudges* by which a smart society can be generated by smart designs. For example, can the digitalization trend facilitate a design of the *choice architecture* so that better decisions can be nudged (Thaler & Sunstein, 2008)?

The questions outlined above are basically applicable to every new technology, not just the digital ones. The relationship between technology and behavior is bidirectional. Behavioral rules or decision making processes can determine how technology is diffused (i.e., the diffusion dynamics). In turn, the availability of a new technology can, or can be designed to, bring about changes in humans' decision making routines or heuristics in a non-trivial way, for example, the great involvement of decision support systems and data-mining tools in decision making, thanks to the advances in high-performing computer technology (Soares de Mello & Namorado

Clímaco, 2015). Therefore, before we proceed further, it is imperative to know how digital technology is different from other technologies and hence deserves a unique treatment. To answer this question, we shall first present one essential assertion that makes digital technology and the shaped digital society unique. We shall then discuss and reflect upon the validity of this argument.

The rest of the chapter is organized as follows. In the second section, we first review the possibility that the digital society has a characteristic to converge to a frictionless economy. We then review some fundamental limits which may cause the path to deviate from convergence. One related issue is the well-known information overload and choice overload problem. The third section shows why these problems may remain even in the digital era. One reason for that is the powerful information pooling mechanisms supported by Web 2.0. The fourth section reviews the information aggregation mechanism in the digital society, known as big data. We address the behavioral causes and consequences of big data in light of Hayek (1945). The fifth section, in view of the recent spread of peer production, crowdsourcing, and crowdfunding, addresses how the powerful crowd matching mechanism provided by the digital society has helped promote prosocial behavior. The final section gives the concluding remarks.

A frictionless economy?

The role of information had been ignored by economists for a long time. Many standard doctrines such as perfect competition and the no-arbitrage condition are built upon some assumptions for fluid information flow. These assumptions had been taken for granted until the rise of research under the discipline known as *economics of information and uncertainty* in the 1960s (Hirshleifer & Riley, 1979). The formation of this field basically recognizes that it is imperative to distinguish the economic theory built upon the assumption of complete information from the one built without this assumption. The information-imperfection awareness in economic theorizing inevitably has promoted economists to clothe their models with considerations of searching behavior (McCall, 1970), uncertainty (Shackle, 1968), ambiguity (Ellsberg, 1961), learning (Cross, 1973), expectations, and various cognitive biases and heuristics (Tversky & Kahneman, 1974), which in turn partially contribute to the body of behavioral economics. Hence, if behavioral economics is partially built upon the assumption that the information is imperfect, then it is high time to examine whether the nature of imperfect information remains unchanged under the digital society.

The key assertion to be proposed and to be open for debates at the outset is that digitalization is a process toward *perfection* in the sense of *perfect information* and a *frictionless market,* dubbed the *perfect-economy assertion.* The perfect-economy assertion starts with the perception that a digital society creates an information-abundant environment in which each agent can access tremendous information with negligible costs. For example, the information regarding prices and quality has become much more easily available in a digital society than in a conventional economy. In addition to big information, there are various searching robots, known as *pricebots* and *shopbots* (Smith, 2002), and various *price comparison websites* (Ronayne, 2015), designed to help consumers find the lowest prices. On top of that, there are online interviews (Chatterjee, 2001), archived as a part of recommendation systems, and various words of mouth, mediated through social media networks, that make it easier for consumers to ascertain the expected quality of goods or services. In a sense, we have all become avid users of databases and search engines. Ideally, an economy evolving with increasing digitalization brings us closer to an economy with perfect information. Hence, the day might come when, in making a purchasing decision, each consumer may access all available commodities associated with the respective prices and quality on his/her smartphone.

Given that information, some smartphone applications (apps) can even automate the default (the optimal) decision for the consumer.

Is the above smart economy realizable, or is it only limited to Hollywood science fiction movies? On this issue, we propose the *non-convergence assertion*. The reason why a digital society will not converge toward a perfect-economy is mainly because of the *description complexity* of the goods, services, jobs, and capabilities. If all of what can be traded in goods and labor markets is in a finite-dimensional space, that is, the familiar R^n space, with time-invariant attributes, then the digitalization of all tradable goods or labor can be a matter of time, and a perfect search or match with the assistance of some highly performing robots can be possible.

However, not all goods and services can be perfectly captured by a vector of real numbers, and, when they are not, verbal descriptions become indispensable. Nevertheless, unlike automated search over Euclidian space, automated search over spaces of verbal descriptions or texts involves not just syntactic issues but also semantic issues. The current text mining techniques are still quite short in handling the latter. Considering the situation where a job searcher can freely describe his preferred jobs and the compensation package, but his verbal descriptions of job preference may not be entirely captured by the robot, because of the semantic difficulty, and hence the search cannot be fully automated. Under this situation, human involvement cannot be waived. What can be even worse, while rather realistic, is that many events are *undescribable*, also known as *complex events*.[2] On this occasion, human involvement in the search process is not entirely replaceable by machines. It is true that digital societies may not free human involvement in many decision making processes, but would it at least make it easier for humans to make decisions and hence enhance human welfare? In the following, we shall argue that the automated search involving humans can end up with a case of *the second-best theory*.[3]

Information and choice overload

Given the prevalence of complex or undescribable events, objects, or products, it is hard to make search robots harness what the host wants. In this case, the search robot will frequently generate a long list of possible relevant choices, which can trap decision makers in the familiar paradox of choice (Schwartz, 2003). The paradox originates from a series of human-subject experiments which address the behavior related to choice conflicts, choice aversion, or choice deferral. Obviously, in this situation, the subject is not well motivated to make a choice and, instead, prefers indefinite procrastination or simply not to make a choice.

In the literature, the paradox of choice is formally known as the *choice overload hypothesis*. The hypothesis says that "an increase in the number of options to choose from may lead to adverse consequences such as a decrease in the motivation to choose or the satisfaction with the finally chosen option" (Scheibehenne, Greifeneder, & Todd, 2010: 73). The choice overload hypothesis was first proposed by Iyengar and Lepper (2000). In their famous jam promotion experiment, Iyengar and Lepper distinguished the designs with psychologically manageable numbers of choices (limited-choice condition), say, six, from the designs with psychologically excessive numbers of choices (extensive-choice condition), say, twenty-four. They found that while the 24-jam table was able to attract more shoppers than the 6-jam one, it did not successfully beef up their purchasing willingness.

The line of research initiated by Iyengar and Lepper echoes well with a separate but earlier research line initiated by Jacoby, Speller, and Kohn (1974) and Jacoby, Speller, and Berning (1974), known as the *information overload hypothesis*. Psychologists believe that when the amount of information provided to decision makers is beyond a threshold exceeding the limited information processing capabilities of decision makers then the quality of decisions made will be adversely affected (Schroder, Driver, & Streufert, 1967). As shown in Figure 18.1, in the initial stage, information load may help decision makers in terms of their decision quality; however, up to some point, say, x_{max}, there is a U-reversal indicating that the further information load may reduce the decision quality, due to a cognitive deficit to process the excessive amount of information. The stage after the U-turn is then perceived as a stage of information overload.

Figure 18.1 is very basic; two qualifications can be added. First, agents are heterogeneous. The threshold or the turning point can be heterogeneous among agents due to their heterogeneous cognitive capacities (Schroder, Driver, & Streufert, 1967).[4] Second, agents are adaptive. From a proactive aspect, they may develop various information filtering strategies to push the threshold forward. This progress may further depend on some innovations in information compression technology. However, information compression, measured based on *Kolmogorov complexity* and *maximal compressibility*, cannot be done indefinitely (Li & Vitányi, 2009). Hence, from a more reactive aspect, agents may rely on various *fast and frugal heuristics* to cope with the overload issues (Gigerenzer & Gaissmaier, 2011).

While the research on information overload was initially conducted outside the context of digital societies, its relevance to digital societies may be even stronger (Lee & Lee, 2004; Chen, Shang, & Kao, 2009).[5] Furthermore, the "primitive" digital societies are operated by the Internet; information suppliers are mainly from the supply side of the economy. However, the modern digital societies are operated by Web 2.0 and various social networks and social media; information suppliers can be all users and cover the entire demand side of the economy.[6] Therefore, we have reasons to believe that the information overload issue can be severer in the modern digital societies. For example, more and more consumers use Web 2.0 tools, such as online discussion forums, consumer review sites, weblogs, and social network sites, to communicate their opinions and exchange product information. This new form of word-of-mouth has now been another source of information overload (Park & Lee, 2009). In this regard, one can expect an increasing relevance of behavioral economics in the digital society.

In fact, recent research on information seeking and searching behavior is greatly influenced by Herbert Simon's notion of bounded rationality (Simon, 1955, 1956). Under the influence of Simon, behavioral economists characterize each decision process with three main stays,

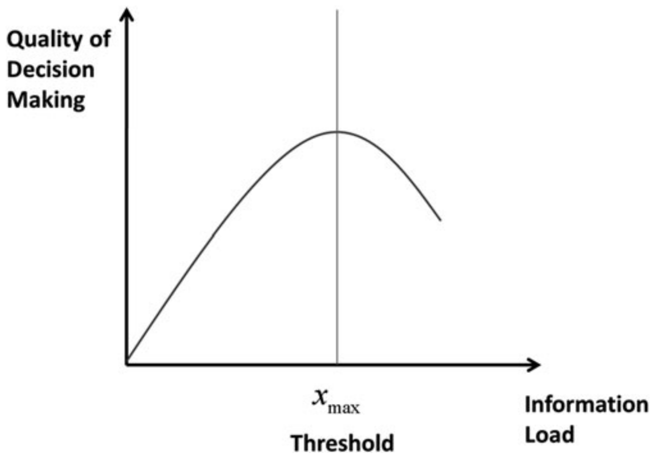

Figure 18.1 Information overload

namely, a *search rule*, a *stopping rule*, and a *decision rule* (Gigerenzer, 2007). It is clear that information seekers in general and Web users in particular are mainly "satisficers" rather than "maximizers". When the object to search is not entirely describable and the search robot fails to pinpoint the desirable target, decision makers are frequently bombarded with an immense list of candidates. In this case, if a stopping rule is not imposed, there may be no limit for human involvement.

To sum up, due to the nature of undescribable objects, digital societies may not be smart enough to bring us closer to the frictionless economy. The information is rich, but it is unclear whether it will be translated into better quality of decisions. Additionally, information overload remains a problem, probably even more severe than before. If so, then like designing choice architecture, the information displayed also needs to be smartly structured before it can beef up decision quality. Not only does this show the significance of "nudging" (Thaler & Sunstein, 2008), but it also indicates that behavioral economics, as a discipline to understand the importance of heuristics and emotion in decision making, may become even more relevant in digital societies.

When Herbert Simon (Simon, 1971) stood on the issue which we currently address, he did not immediately exclude the possibility that a computer may compound the information overload problem instead of solving or mitigating it. He acutely proposed the following general principle:

> *An information processing subsystem … will reduce the net demand on the rest of the organization's attention only if it absorbs more information previously received by others than it produces.*
>
> *(Ibid.: 42; italics, original)*

As we shall see in the next section, it is entirely possible that the digital society may *produce* more than it can absorb.

Big data

One issue related to digital societies and information overload is *big data*. Data become big when our communication, leisure, and commerce have moved to the Internet and the Internet has moved into our phones, our cars and even our glasses, and life can be recorded and quantified in a way that was unimaginable just a decade ago. With the advancement of digital societies, more and more people are placed in this big data or information-rich environment in the following two prototypes.

First, each agent is equipped with some portable digital devices, such as notebooks or smart phones. Each of these devices, through the Internet, is connected to a platform. The platform pools the information received from this and other agents (Figure 18.2, the left panel), and may further aggregate and process this information and then send back signals to these or other agents online or offline to facilitate or *influence* their decisions and communications.[7] Examples abound, such as the United Nations' project on Global Pulse, Google Flu Trends, Google Glass, and Street Bump (Table 18.1). Second, each agent is situated in an environment surrounded by digital devices which may interact with the agent or the portable device carried by the agent (Figure 18.2, the right panel). Based on the on-time information received, the device can provide timely information for the agent or other stakeholders. Examples are BinCam, Environmental Teapot, smart mirror, smart carpet, or smart belt (Table 18.1).[8]

Long before the availability of big data, economists had already noticed the value and the use of big data, although in those days the term was not in the dictionary of economic science. Friedrich

Table 18.1 New data collection device

	Descriptions and Related Research
Global Pulse	Kirkpatrick (2014)
Google Flu Trends	Ginsberg et al. (2009)
Google Glass	Ackerman (2013)
Street Bump	Schwartz (2012)
Traffic D4V	Picone, Amoretti, and Zanichelli (2012)
BinCam	Comber and Thieme (2013)
Environmental Teapot	Marres (2012)
Smart Mirror	Pantano and Nacarato (2010)
Smart Carpet	Aud et al. (2010)
Smart Belt	Shieh, Guu, and Liu (2013)

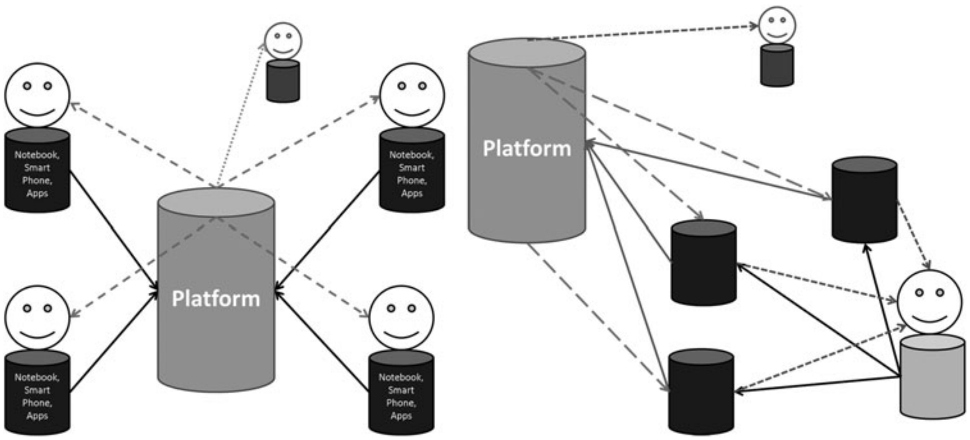

Figure 18.2 Ubiquitous computing (left panel) and Internet of Things (right panel)

Hayek, in his classic work (Hayek, 1937, 1945), rightly addressed this issue. In response to the possible information overload, he was wondering how much we really need to know.

> How much knowledge does he need to do so successfully? Which of the events which happen beyond the horizon of his immediate knowledge are of relevance to his immediate decision, and *how much of them need he know*?
>
> *(Ibid.: 525; italics added)*

The solution that Hayek proposed for the information overload problem is an *information aggregation mechanism*. With the market as an information aggregation mechanism, decision makers may be able to be free from information anxiety (Wurman, 2001) by "*watching the hands of a few dials*, in order to adjust their activities to changes of which they may never know more than is reflected in the price movement" (Hayek, 1945: 527; italics added). In his active participation in the Socialist Calculation Debate, Hayek did not consider that a central planner by incorporating all relevant data into a supercomputer and carrying out the Walrasian tâtonnement process, as suggested by Oskar Lange and Abba Lerner, can be an effective alternative to the market mechanism (Boettke, 2000). It is not even theoretically possible.

From a glance of the smart devices listed in Table 18.1, one can see that a take-off to characterize digital societies is, indeed, *information aggregation*. For example, Google Flu Trends uses search engines to collect unstructured posts, messages, searches, updates, and tweets from the users of social media sites and uses these data to predict influenza patterns ahead of the Centers for Disease Control and Prevention (CDC) and to strengthen public health preparedness. Similarly, the Street Bump app relies on ubiquitous motion detectors which are available in many citizens' smartphones to map out potholes on Boston's roads with almost no time delay without the need for city workers to patrol the streets. It seems that these digital devices are catching every "man on the spot" (Hayek, 1945: 524) and placing them on the screen.

In this way, digital societies may then introduce a *non-market information aggregation mechanism* as the alternative to the conventional market mechanism and it may be even more direct and immediate. With a degree of optimism, one can ask whether the information will be aggregated in such a way that we can envision a future without auto accidents and traffic jams, when human fallibility is kept in check (Picone, Amoretti, & Zanichelli, 2012). In the same vein, would the cobweb model instability due to misalignments of production with lags be avoided in the future? From the current majors of PhD students, can the education system be quickly informed that a decade from now college teachers in humanities will be in short supply (Ehrenberg et al., 2009)? Would various environment, energy and health issues related to poor decisions, due to near-sightedness constraints or the ignorance of possible social and individual consequences, be managed better in a growing digital society?

Needless to say, the list of the above issues above can indefinitely extend, and they have been broached in the recent literature on big data (Morozov, 2014; Harford, 2014; Hargittai, 2015). From the viewpoint of behavioral economics, what concerns us is the possibility or the limitation of non-market information aggregation mechanisms with big data. The essence of Hayek (1945) on information aggregation involves two major functions: *information pooling* and *processing*. Both introduce some difficulties which have concerned Hayek and his contemporaries, but are now equally troubling the big data theorists and pragmatists.

On information pooling, Hayek has emphatically pointed out the tacitness of knowledge (Hayek, 1937, 1952). It is fundamentally difficult to make tacit knowledge explicit. However, even though tacit knowledge is not a problem, information pooling requires individuals' cooperation. On this, Hayek (1945) states

> the knowledge of the particular circumstances of time and place. It is with respect to this that practically every individual has some advantage over all others in that he possesses unique information of which beneficial use might be made, but of which can be made only if the decisions depending on it are left to him or are made with his *active cooperation*.
>
> *(Ibid.: 521–2; italics added)*

The required active cooperation has challenged the incubation of many big data ideas. For example, it has been documented that one problem for BinCam, as a solution to waste control and recycling enhancement, is that engagement with social media remains low (Comber et al., 2013). In economics, this issue is known as a *thin market*. The performance of the prediction market, an idea directly inherited from Hayek (1945), is known to be adversely affected by market thinness (Berg et al., 2008). From a statistical viewpoint, we do not demand that the whole population or a very large sample serve as the foundation of decisions, but small samples may introduce biasedness, which can ruin the performance of prediction markets as well as big data intelligence.

Assume that all people are cooperative: they join social media and carry smartphones. Then ubiquitous computing,[9] as demonstrated in Figure 18.2 (left panel), will paint a picture of the world with immense detail. In this sense, big data is the modern equivalent of a microscope. When the amount of information is measured by zettabytes or even yottabytes, we may actually be totally blind unless some automated procedure can mine the hidden gold for us. However, in Web 2.0, the main data type is texts, images or videos, and not just numbers. Intelligent algorithms are required to recognize, interpret, and process opinions, attitudes, sentiments, emotions, and implications inherent in natural language, images, and videos. The current state of the art with its reliance on searching for key terms, phases, or geometric patterns is, at best, rather limited for us to access the knowledge inside the box.

Crowd matching

While human nature remains a long-standing debatable issue in philosophy, from Aristotle, Plato, Mencius, and Xunzi to Thomas Hobbes and Jean-Jacques Rousseau, the recent interdisciplinary scientific studies on prosocial behavior tend to suggest that it would be oversimplified or even misleading to assume that humans are selfish (Schroeder & Graziano, 2015). Even those who hold opposite views may agree that prosocial behavior can be enhanced or corrupted through different social institutions or social structures. It is, therefore, interesting to inquire about the possible impacts of digital societies on prosocial behavior.

Earlier we mentioned that digital societies may enhance the quality of decisions by providing more "smart" information aggregation (pooling and processing). This implies that this "smart" information aggregation mechanism may enhance *pairing* or *grouping* decisions; after all, the other side of the information aggregation mechanism is the *matching mechanism*. Digital societies have already helped match demand and supply through a large pool of products with the aid of online customer reviews (see the second section). In economics, matching theory starts from dating (Gale & Shapley, 1962) and, over the last two decades, we have seen that online dating has revolutionized these "economic" activities by providing participants with more opportunities to access potential partners. As we have mentioned in the second and third sections, whether this will facilitate decision making depends on how efficiently information is aggregated. If the information to be pooled is not overwhelming and hence can be effectively processed, it may be possible that online dating can help participants make better decisions (Hitsch, Hortaçsu, & Ariely, 2010; Rosenfeld & Thomas, 2012; Konrad, 2015).

In this section, we consider a more general form of matching—matching a team or a crowd since this is a place where we probably can closely observe how people cooperate, sometimes altruistically or voluntarily, to achieve some common goals that could not be realized alone. The three most shining demonstrations are *peer production*, *crowdsourcing* and *crowdfunding* (Figure 18.3).

Peer production refers to the activity whereby individuals voluntarily collaborate to produce knowledge, goods, and services. This form of production, distinguished from production activity through markets and hierarchies, is the third alternative of the production paradigm (Benkler, 2002, 2006). The work, from the time of its inception by some initiators, can be constantly modified and extended by a dynamically evolving self-organizing team comprised of volunteer workers who have no binding commitments to the team. This emerging production paradigm in digital societies, also known as *digitally enabled peer production*, has been an important source of value or wealth creation and public goods provision in many domains, such as open source

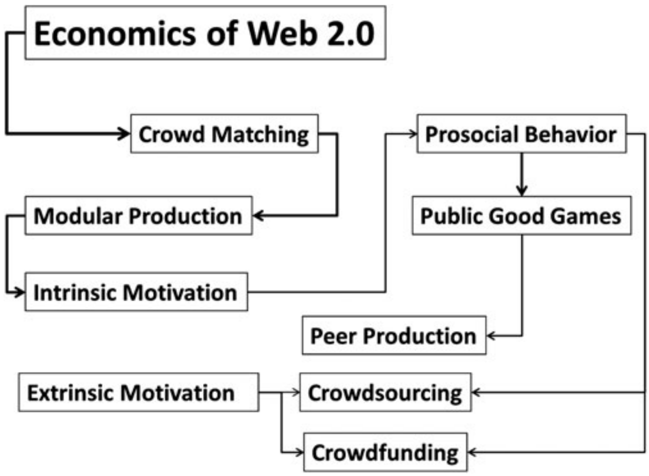

Figure 18.3 Prosocial behavior in the form of the digital society

software projects, citizen science (Bonney et al., 2014; Franzoni & Sauermann, 2014), library science, politics, education, journalism, and culture. It is still not clear as to the limit of the applicability of digitally enabled peer production in other domains (Kreiss, Finn, & Turner, 2011), but a required key element is *modular production* or, simply, *modularity*.

Modular production is an idea largely ignored in mainstream economics, although it can be long traced back to Herbert Simon (Simon, 1962), specifically, in his story on the competition between two watchmakers, Tempus and Hora. A technical formulation of the modular economy and modular production is given in Chen and Chie (2007), Chie and Chen (2013), and Chie and Chen (2014). Technically speaking, a production process is referred to as modular production if it can be modeled by a *context-free grammar*. By a context-free grammar, each work (product), depending on the grammar (technology), and the current alphabets (materials, knowledge, or expertise), can be reshaped and extended; Wikipedia provides such an example. Even though the work is completed, it can still be reused as a module of another more synergetic work or product; open source software projects are cases in point.

Modular production has already existed long before the advent of digital societies. What digital societies have done is to facilitate modular production by efficiently matching various modules distributively owned by different volunteers. In terms of the context-free grammar, the minimal module is an alphabet, which indicates that the threshold for volunteer work can be low. In other words, digital societies allow peers with skills for specific modular tasks to be easily matched in various public good projects, and the match can be so fine that even the minimum threshold required for the corresponding public good, perceived as a threshold public good game, is low.

The access to a great diversity of public good games helps the formation of intrinsic motivation for a heterogeneous population of agents, whereas the low threshold, acting in a form of "even a penny will help", promotes volunteerism. The latter is the familiar *legitimization of paltry donations*, which satisfy the donor's need for self-presentation of being helpful and socially responsible (Shearman & Yoo, 2007; Guéguen, 2013). In sum, digital societies enable efficient matches of intrinsically motivated volunteers; hence, it helps promote prosocial behavior. Our theoretical explanation above is basically consistent with the experimental findings of Algan et al. (2013), who showed that reciprocity and social image are both strong motives for sustaining cooperation in peer production environments, while altruism is not.

The second form is crowdsourcing (Figure 18.3). Crowdsourcing is a term coined in 2006 by Jeff Howe (Howe, 2006, 2008), who defined it as the outsourcing of a function or task traditionally done by a designated agent to an undefined network of laborers carried out by a company or a similar institution through an open call for solutions over the Internet or social media. Crowdsourcing is, therefore, another collaborative model of production which involves prosocial behavior. However, it is different from peer production in its property regime. As mentioned earlier, peer production is mainly used to produce public goods or commons, such as Wikipedia or open source software; however, in crowdsourcing, both inputs and outputs are governed by proprietary or contractual models. Some frequently cited examples of crowdsourcing are Amazon Mechanical Turk, an online labor market (Paolacci, Chandler & Ipeirotis, 2010), and reCAPTCHA, which uses optically scanned book fragments as gateways to secure services (von Ahn et al., 2008).

Crowdsourcing is not new to economists. This development is in the vein of the market mechanism as the efficient use of knowledge (Hayek, 1945). Before the advent of Web 2.0, we had already seen two stages of its early development in economics, namely, experimental markets and prediction markets (Arrow et al., 2008). The idea of creating a *market* such that knowledge distributed over the crowd can be used (pooled and processed) has become the idea of creating a *platform* to do that. In fact, the prediction market can be considered as the earliest form of crowdsourcing. Since the middle 2000s, we have experienced the quick development and evolution of various forms of crowdsourcing. Partially because of this trend, even the prediction market has evolved into its second generation, namely, the idea market (Slamka, Jank, & Skiera, 2012).

Working a crowd begins with constructing a crowd; the motivation for participating in a crowd becomes an important issue. On this issue, while extrinsic motivation is found to be crucial in many crowdsourced domains, intrinsic motivation or the internalized extrinsic motivation is also found to be key driver of the formation of crowds (Brabham, 2010; Füller, 2010; Roth, Brabham, & Lemoine, 2015). From these studies, people participating in crowdsourcing are *not just for the money* (Frey, 1997). Some are participating for the love of the underlying community, for the enjoyment of being jointly creative, or, more generally, for the pleasure of being part of the process of a participatory culture. Through the Schelling–Axelrod model (Axelrod, 1997), we know that homophily, in the form of sharing some common interests, may play an important role in giving a cohesive structure to the formed culture and community. Therefore, crowdsourcing shows again how the proliferation of the Internet, the explosion of social media, and matching technologies have promoted prosocial behavior, accompanied by a cultural formation process.

The last form is crowdfunding (Figure 18.3). Crowdfunding platforms allow the kind of search and assembly of information that can bring up crowds of otherwise diverse investors with similar focuses to jointly turn entrepreneurs' ideas into a reality. Examples of crowdfunding platforms include Kickstarter, Indiegogo, RocketHub, Fundable, Crowdfunder, etc. The starters of small and medium-sized businesses may find it easier to succeed through the kind of communication and search that those platforms provide. As Robert Shiller pointed out, crowdfunding draws on modern behavioral economics (Shiller, 2013). It is "based on concepts of motivating drives in people, on their ability to respond to incentives, and the diversity of types of people that may be brought together creatively in enterprises" (Ibid.: 80).

The two essential characteristics which enhance prosocial behavior in peer production also appear here, namely, fine modularity and low threshold. Some fundraisers modularize their project at a fine level and rank the modules by the required investment, from moderate size to pocket money. This division helps distinguish investors not only by their shared vision but also by their financial affordability. Hence, just like the paltry contribution seen in peer production, the threshold required for a crowdfunded project can be low. For example, in Kiva, a non-profit micro-loans organization with a mission to connect people through lending to alleviate poverty, one can loan merely $25 to a seamstress in Guatemala or to a pig farmer in Senegal.

Crowdfunding differs from the conventional capital markets in the sense that through Web 2.0 it is embedded with a kind of participatory culture. A number of studies have already noticed the significance of intrinsic motivation to invest in crowdfunded projects. For example, Gerber, Hui, and Kuo (2012) found that in addition to anticipated extrinsic motivators, such as securing funding (for creators) and consuming products and experiences (for backers), participants were also motivated by social interactions realized through crowdfunding platforms, such as the strengthening commitment to an idea through feedback and feelings of connectedness to a community with similar interests and ideals. Beaulieu and Sarker (2013) conducted a discourse analysis of the contents over the course of a crowdfunding campaign. They argued that understanding the creation of meaning is important because this meaning inspires backers not only to contribute financially to a given project but also to share the project within their own social networks. The intrinsic motivation may become even more important when we consider a special type of crowdfunding, namely, micro-crowdfunding or civic crowdfunding, in which a crowdfunding concept is used to encourage a community to act to solve critical social problems (Davies, 2015).

Concluding remarks

In this chapter, we provide probably the first comprehensive reflection on digital societies, or so-called smart societies, from the viewpoint of behavioral economics. What particularly concerns us is whether smartness, if there is any, can be translated into goodness at both the individual level and the social level. We basically address two issues along these lines. First, we ask whether a "smart" society can actually enhance the quality of individual decisions, either through more information or better nudges. We point out that, although a "smart" society is strong in terms of information pooling as manifested by big data, it is not immediately clear whether this vastly pooled information, particularly in the form of transcripts, audio, or video data, can be efficiently processed.

Therefore, based on Simon's economics of attention (Simon, 1971), the net gain of a "smart" society is not guaranteed to be positive, and hence the concern with the information overload or choice overload hypothesis remains or is amplified. When that happens, we should be alerted to the situation where a "smart" society may not make decision making easier, but harder. This is mainly because people are more easily exposed to an information-rich environment, while at the same time the intelligence tools which can help them grasp the essence of the big pile of various types of data may not keep pace with the speed of pooling. Facing this conundrum, agents may have heuristics to which they can resort to circumvent this situation. Some of these heuristics can be fast and frugal, but some can be herding and biased. While it is now a trend for people to keep on watching the dynamics of everything from their smartphones as if they were checking for the presence of any arbitrage condition, we have yet to see up to when they will find that the leisure which they have given up for this "work" may not be worth the effort made. However, under limited attention, smartphones and the "smart" society can cause the entire society to become addicted to this "diligent" social norm and may have adverse effects on the quality of life and degree of happiness (Lohmann, 2015).

From the social viewpoint, we notice that a "smart" society is strong in its matching mechanism. In fact, this enhancement is not simply due to technological feasibility, but more to the participation of humans (the crowd). Web 2.0 enables agents to self-organize through search and discovery. This function is also provided by the conventional market (Hayek, 1945), but Web 2.0 makes this function even more powerful, thanks to various platforms and social media. As a result, it makes Adam Smith's invisible hand bigger; in fact, it is the search and discovery process initiated and driven by humans that modularizes production to achieve a finer division of labor and then pack the platforms in a well-structured manner.

Hence, on the one hand, this enhanced matching mechanism helps people to discover what they are initially endowed with in terms of labor, skills, and talents; some of these "advantages" naturally become part of their intrinsic motivation to participate in market activities, a part to which mainstream economics has paid less attention. On the other hand, since the matches are flexible and adaptive with size, this facilitates the formation of a crowd. This promotes prosocial behavior because the contribution from each participant can be small, and the aspired intrinsic motivation is sufficient to incentivize such size of contribution. Peer production, crowdsourcing, and crowdfunding can all or partially be seen as a consequence of prosocial behavior.

In sum, digital societies will neither create a frictionless economy nor an omniscient agent, and that in fact enhances the relevance of behavioral economics. It provides us with better technological support to design various nudges or choice architectures, and a more flexible space to design field or policy experiments to realize various prosocial behaviors by coordinating good incentives. In his forward to the second edition of Axelrod's book, *The Evolution of Cooperation*, Richard Dawkins began with "THIS IS A BOOK OF OPTIMISM. But it is a believable optimism, more satisfying than naïve, unrealistic hopes of pie in the sky (or rapture in the revolution)" (Axelrod, 2006: xi; capitals, original). Since Axelrod (1984), game theory has constantly shown that social networks or social structures that facilitate prosocial behavior do exist and can emerge from network evolutions.[10] Digital societies have demonstrated their great potential to form such social networks.

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Notes

1 Since the term "smart society" is often used with the term "digital society", in this chapter they shall be used interchangeably. To be exact, the reader should keep in mind that smart society used in this chapter can be given quotation marks, that is, "smart" society, due to the existence of both optimism and skepticism toward the future of digital societies. Therefore, with this understanding, we do not intend to make a further distinction between those digital societies which are considered to be smart and those which are not.

2 The undescribable or complex event has been an idea well established in the incomplete contract literature (Chen, 1992; Al-Najjar, Anderlini, & Felli, 2006; Kunimoto, 2008, 2010).

3 The second-best theory was first formulated by Lipsey and Lancaster (1956). It says that if we are away from the optimal conditions on more than one dimension, then satisfying some optimization conditions, but not all of them, is not guaranteed to be superior to a situation in which fewer conditions are fulfilled. For a survey, the interested reader is referred to Lipsey (2007).

4 See Chen (2015), part VI, for a comprehensive treatment of this subject.

5 The reader, however, should be reminded of some mixtures of the results in the literature on these two overload hypotheses, namely, information overload and choice overload. The interested reader is referred to the existing survey articles (Eppler & Mengis, 2004; Scheibehenne, Greifeneder & Todd, 2010).

6 O'Reilly & Battelle (2009) give a systematic guide to the origin and the development of Web 2.0.

7 It is important to emphasize that in some cases, such as the Environmental Teapot, BimCam, smart mirror (Table 18.1), the processed information or output signals are not just passively used to help decision makers make a decision; it may even actively persuade or "coerce" them to behave in a certain way. This design involves the elements of both social norms and social preferences to place decision-makers in a more social-awareness decision frame. This kind of design is also known as *persuasive technology* (Fogg, 2002; Hamari, Koivisto, & Pakkanen, 2014).

8 More generally, any object can be attached to a digital sensor to constantly collect surrounding information, from temperature, humidity and chemical particles to pedestrian intensity, mass psychology and public conversations. All local information can be pooled in a platform, also known as the *Internet of Things* (Westerlund, Leminen, & Rajahonka, 2014), to get a grasp of the global environment.

9 The term *ubiquitous computing* was first introduced by Mark Weiser in 1989, to distinguish it from conventional desktop computing (Weiser, 1991). For recent developments more related to the scope of this chapter, the interested reader is referred to Kinder-Kurlanda & Nihan (2015).

10 For a literature review of the pile of studies, the interested reader is referred to Namatame & Chen (2015).

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