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Big Data, Scarce Attention and Decision-Making Quality

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Abstract Big data technology enables us to access tremendous amounts of information; however, individuals cannot process all available information due to the bounded attention. The impact of this tension upon information seeking and processing behaviors and the resultant decision-making quality is still unclear. By agent-based simulation, we explicitly model the endogenous information choice in a sequential decision-making process, where individuals choose independently how much information and what type of information (shallow information such as the popularity a product, or deep information such as the expected utility of a product) is to be used. It is found that when the information is costly, only a small part of the individuals use deep information and only limited pieces of it, and other individuals simply follow the majority choice. The decrease in the cost of information cost due to big data can encourage individuals to make use of more information, resulting in a better overall decision quality. However, if the big data only reduces the cost of shallow information but not that of the deep information, the decision quality is diminished because more individuals are induced to adopt the herding strategy.

Keywords Big data · Attention Scarcity · Information Aggregation · Agent-based Model · Herding

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1 Background and Motivation

We are entering an age of big data (Mayer-Schönberger, 2013). With the advancement of information and communication technologies, especially Web 2.0, ubiquitous computing, wearable devices, social media and the Internet of Things (IoT), more and more people are being placed in a big data or information-rich environment (Chen and Venkatachalam, 2016). 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 (Chen et al, 2017). Up to 2007, the information capacity of the world’s storage was 295 exabytes, requiring a stack of discs reaching to the moon and then a quarter of the distance back from the Earth to the moon (Hilbert and Lopez, 2011). According to Internet Live Stats, a website of the international Real Time Statistics Project, every second, approximately 7500 tweets are tweeted; 44000GB of data are transferred through the Internet; about 60,000 Google queries are searched; and more than 2.6 million emails are sent (InternetLiveStats, 2017).

Despite the abundance of information, our capacity to process it is limited. Substantial evidence suggests that humans are limited in their ability to process information and to perform multiple tasks simultaneously (Pashler and Sutherland, 1998). Kahneman (1973) argues that individuals are endowed with a certain mental capacity, so that attention spent on one task must reduce attention available for other tasks. Some physiological psychology research has sought to understand the neural basis of the limited attention capacity. Dux et al (2006) find evidence indicating that a neural network of frontal lobe areas acts as a central bottleneck of information processing that severely limits our ability to multitask. Tombu et al (2011) provide evidence supporting the existence of a “unified” attentional bottleneck (including the inferior frontal junction, superior medial frontal cortex, and bilateral insula) that limits operations of both perceptual encoding and decision-making. As for evidence regarding the limited attention in information seeking and processing, Agosto (2002) shows experimentally that young people only view a limited number of websites for a limited time before making decisions because of time, cognitive, and physical constraints, and Browne et al (2007) reveal that people utilize a number of different stopping rules to terminate searching for information online.

The tension between the attention scarcity and information richness has already been addressed by Herbert Simon as far back as in 1971 (Simon, 1971).

... in an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently
among the overabundance of information sources that might consume it. (Ibid., p.40)

As a matter of fact, when measuring the cost of information, the key concept in economics of information, it is this attention scarcity that plays a determining role.

In an information-rich world, most of the cost of information is the cost incurred by the recipient. It is not enough to know how much it costs to produce and transmit information: we must also know how much it costs, in terms of scarce attention, to receive it. (Ibid., p.41)

Obviously, the role of attention scarcity in an information-rich environment as initially observed in Simon (1971) is more pressing in our modern times than half a century ago. In light of Simon’s pioneering observations, the nature of this tension raises two fundamental intellectual challenges.

(1) from the microscopic viewpoint, how does the increasing tension between information richness and attention scarcity impact the behavior of an individual decision maker in terms of his/her employed decision heuristics?

(2) from the macroscopic viewpoint, how does the founded behavioral pattern contribute to information aggregation over big data and what is the resultant quality of decision making at a societal level?

While the literature has paid much attention to the first issue (see the above review), it is the second issue that seems to be more subtle to economists. This is so because big data is widely perceived as a promising way, familiarly known as the *wisdom of crowds*, to enhance decision-making (Surowiecki, 2004); nonetheless, caution is normally kept under the shadow of the *stupidities of herds* (Bonabeau, 2004) or *shallow thinking* (Carr, 2011), which indicate that the decision-making quality can greatly deteriorate as well.

However, as Simon et al (1987) well noticed, the subtlety of the second issue cannot be properly addressed without integrating it with the first issue. The mainstream approach based on the device of the representative agent is hardly applicable.

In applying our knowledge of decision making and problem solving to society wide, or even organization-wide, phenomena, the *problem of aggregation must be solved*; that is, ways must be found to extrapolate from theories of individual decision processes to the net effects on the whole economy, polity, and society. Because of the wide variety of ways in which any given decision task can be approached, it is unrealistic to postulate a “representative firm” or an “economic man”, and to simply lump together the behaviors of large numbers of supposedly identical individuals. (Ibid., p.26; Italics added)

Very much in this vein of Simon, in the current paper, we propose an agent-based approach to study the social consequences of attention scarcity in the era of big data. Agent-based modeling is a kind of complex-adaptive-system (CAS) research paradigm (Chen, 2016). Its intellectual connection with Simon
has been reviewed in Chen and Kao (2016). Using agent-based modeling, we basically regard the information aggregation over big data as a complex adaptive system composed of a large number of users who are interacting with each other, from which the macro-level patterns emerge.

1.1 Earlier work

In the literature, formal studies addressing the social consequence of attention scarcity in an information-rich environment are rarely found to exit. Vriend (2002) is the only related work known to us, and while his work is more on information aggregation, attention scarcity is, nonetheless, implicitly mentioned.

Vriend (2002) provides an agent-based study of information aggregation when agents (users) have to make a choice with the presence of big data (other users’ choices and experience). Specifically, he considered a society in which a finite number of consumers are repeatedly offered a binary but different kinds of choice. To make a choice, agents can learn by surfing over the Internet (platform) to see the choices and/or experiences of the preceding users. Vriend assumed that agents could get access to all of this information (the big data assumption), including both the choices and experiences; nonetheless, their attention scarcity severely restricts their view scope, to be precise, a finite random sample with an exogenously given number of observations. Vriend then introduced two families of heuristics to process this finite number of observations, one concerning the number of users, and the other concerning the users’ experience. As shall become clear later, the former can be regarded as the herd-based strategy, whereas the latter can be regarded as the utility-based strategy. Agents then constantly try these two families of strategies using the familiar reinforcement learning. Two major findings stand out: first, from a mesoscopic point of view, the reference to these two families of strategies is not even and agents following herd-based strategies tend to make up the majority; second, from a macroscopic viewpoint, with regard to the decision quality, while most of the time the agents who made the right choice (the superior choice) constituted the majority, occasionally, disasters characterized by the large crowd making the inferior choice, the systematic failure, are also found to happen. On these grounds, Vriend showed that the wisdom of crowds and the stupidity of herds could co-exist, a result having rich implications for the information-rich society.

Vriend’s model provides a framework to study how the Internet and big data influence the individual’s information-processing behavior and how they in turn affect the information aggregation efficiency. However, Vriend did not go further to address the possible interplay between information-processing behavior and the view scope (the assumed attention scarcity), as if the former were insensitive to the latter. Under the same big-data assumption, Yu et al (2018) extended the Vriend model along a range of view scopes. They found that agents’ information-processing heuristics, specifically, the mesoscopic structure of the two families of strategies, are not invariant to the giv-
en view scope. When the view scope is small, the dominant heuristic is the herd-based strategy, echoing the result of Vriend (2002); nonetheless, when the view scope gets broader there is an increasing tendency to switch to the utility-based strategy. In this regard, Vriend’s result is not insensitive to the assumed attention scarcity.

1.2 Our departures

Despite the dependence of information-processing behavior on the assumed attention scarcity (attention capacity), an important fact ignored by both Vriend (2002) and Yu et al (2018) is that the information-processing heuristic per se also requires attention. It is perceivable that the herd-based strategy, which only counts the number of users, can be less demanding for attention than the utility-based strategy, which requires performing the task of content analysis, such as reading on-line reviews. The first departure of this paper is, therefore, to take into account the different attention intensities associated with different information-processing heuristics. In this paper, as motivated by Simon (1971), a linear “cost” function of attention is proposed to represent a kind of disutility when more deliberate heuristics are used. To further consider the possible progress of big-data analytical technologies, we attempt to apply a wide range of values for the cost parameters.

This explicit modeling of costs of attention allows us to further address the endogeneity of the view scope, which, in Yu et al (2018), is given exogenously and held homogeneously by all agents. Alternatively put, the second departure of this paper is to allow each agent, in addition to information-processing heuristics, to also learn how much attention to draw to cope with the given binary decision problem when he/she is put in an information-rich environment. With these two departures and hence the extending framework, we then study the mesoscopic structure of information-processing heuristics and the macroscopic information-aggregation efficiency. Are the heuristics necessarily simple, such as following the herd, and is the decision quality necessarily good, hence having the wisdom of crowds?

The remainder of this paper is organized as follows. Section 2 introduces the model. Section 3 presents the simulations and results. A discussion and conclusion are provided in Section 4.

2 Model

An important characteristic of big data economics is that individuals make decisions based on a large volume of data and at the same time produce new data. Imagine that two new products are released online at the same time, and individuals, in a sequential manner, need to choose one of them. In the environment of big data, each individual’s choice or consuming history can be digitally archived, and some of the consumers may further write reviews
about the products. Such information is ready to be accessed by others with an amount of time and effort, using the endowed information and communication technology. Vriend (2002) presented an agent-based model for this sequential decision-making process with each agent observing a fixed number of other agents’ actions (view scope is fixed), whereas Yu et al (2018) extended this model by allowing for different view scopes. In this section, we shall review the basic model as suggested by Vriend (2002) and expand it in the direction of Yu et al (2018). Our proposed model has three constituent parts, namely, the (binary) choice problem (Section 2.1), the decision heuristics (Section 2.2), and the learning behavior (Section 2.3). We shall elaborate on each of them in the subsequent subsections.

2.1 Binary choice problem

The model has a population of \( N \) decision makers (consumers, in our case). In each period, each of them, with a randomly pre-specified order, is presented with a binary choice problem. In this problem, two competing items of the same product which has never been experienced by these consumers are offered, say, two restaurants, two movies, two detective stories, two iPhones, etc. Each item, say, \( i (i = 1, 2) \), is characterized by its expected utility that can be generated to the consumers, say, \( EV_i \). \( EV_i \) is randomly determined following a uniform distribution \( U(0.25, 0.75) \). Given the expected value \( EV_i \), the utility that a specific consumer can actually experience from consuming this item is determined by a draw from the uniform distribution \( U(EV_i - 0.25, EV_i + 0.25) \). The stochastic nature of the generated utility can be interpreted as the preference heterogeneity among these consumers or as the quality uncertainty of the products. For example, for a given item \( i \), if its characterized \( EV_i \) is 0.60, then the utility which can be actually gained from consuming it ranges from 0.35 to 0.85, with each of these utility levels being equally likely to occur.

When facing the aforementioned choice problem, each individual consumer has no experience with these two competing offers; nonetheless, the sequential nature of the choice environment allows him/her to observe the choices of a sample of preceding consumers and/or their realized utilities (their experiences with the product).\(^1\) Likewise, his/her choice and the outcome (the realized utility) can become the reference for the subsequent consumers. His/her followers then ditto the same procedure until all \( N \) consumers complete their choice.

The choice problem described above will be repeated in multiple periods, say, \( T \) periods. In each period, the product and hence the choice problem remains novel. In other words, the two items in each period are completely independent of the two items in other periods. Basically, the choice problems across different periods of time are fundamentally different, despite their binary structure remaining the same. The decision-making behavior addressed in the

\(^1\) While, in principle, agents can observe the choice and the realized utilities of all preceding consumers, their attention scarcity may not allow them to do so exhaustively. See Section 2.2 for the details.
Vriend model is, therefore, not on one specific binary choice problem, but on a meta level of the binary choice problem, namely, how to use information to solve any binary choice problem. In the next subsection, we shall introduce some decision heuristics at this meta level.

2.2 Decision strategies

As stated above, the decision maker (consumer) needs to figure out a heuristic to learn from others at a meta-level so as to cope with the constantly-presented novel binary-choice environment. In our basic setting, each heuristic contains two fundamental elements, i.e., its \textit{width} and \textit{depth}; the former refers to \textit{how many to observe}, denoted by $n$, and the latter refers to \textit{how much to know}. These two are also the two fundamental dimensions that characterize the data-driven decision heuristics in the big-data era.

Vriend (2002) did not consider the first element, and only focused on the second and distinguished the information by its degree of shallowness (depth), which in Yu et al (2018) is further termed as \textit{the herd-based strategy} (the shallow one) and \textit{the utility-based strategy} (the deep one), to be elaborated on later. Without considering the first element, Vriend (2002) was able to use a pool of 31 heuristics to differentiate each family of strategies by its fine constituents. Since our model also needs to deal with the first element, we deviate from the Vriend model by only focusing on the typical kind of strategy for both families. This simplification in turn allows us to bring back the missing element on the width of the heuristics. In brief, we extend Vriend (2002)’s and Yu et al (2018)’s one-dimensional model to a two-dimensional one by augmenting both shallow and deep learning with a width parameter ($n$).

The competition between the two families of heuristics at the meta-level, namely, shallow learning and deep learning, is a key to understand the emergence of the wisdom of crowds and the stupidity of herds (Vriend, 2002; Yu et al, 2018). The shallow learning essentially means following the herd, and hence is represented by the herd-based strategy (HBS). Following the herd or following the majority is a behavioral model extensively used in the literature on agent-based computational economics. An agent who adopts the herd-based strategy, the HBS agent, observes what his/her preceding agents chose and takes the side of the majority. Algorithmically, an HBS agent with a width of $n$, or, for brevity, an HBS($n$) agent, observes $n$ randomly selected preceding consumers and takes the more popularly-chosen item based on this random sample. If the degree of popularity of both items is the same, he/she will randomly select one of the two by throwing a fair coin. In the case where the number of the preceding consumers, $x$, is less than $n$, the HBS($n$) agent will be “forced” to act as if he/she were an HBS($x$) agent.

The herd-based strategy only requires the information about what other agents did, but not what they actually experienced. In the case of on-line customer reviews, the HBS agent is only interested in knowing the very simple
statistics, namely, the head count of each item; in this sense, it is “shallow”. The utility-based strategy (UBS), on the other hand, requires information about the actual experience or the realized utility of the preceding consumers. In the case of on-line reviews, it may involve a painstaking effort to read the sampled review reports. Algorithmically, an agent who adopts the utility-based strategy, or the UBS agent, makes the decision based on the information of both the choices made by his/her preceding agents and their realized utilities. A UBS agent with a width of \( n \), or a UBS(\( n \)) agent, observes the choices and the utilities of \( n \) randomly selected preceding consumers. If, in this random sample, both items were active, the agent will calculate the average realized utilities from these preceding users associated with each item, and choose the item that has a higher average utility. If the average utilities of the two items are the same, the UBS(\( n \)) agent will randomly select one of the two items, using a fair coin. If in the random sample only one item was active, the UBS(\( n \)) agent will choose the only active item if its average utility is larger than a pre-specified reference point\(^2\); otherwise, he or she will choose the idle item. As in the case of the HBS(\( n \)) agent, if there are insufficient preceding consumers, i.e., \( 0 < x < n \), the UBS(\( n \)) will automatically be carried out in the form of UBS(\( x \)).

Obviously, the attention required to be drawn to the above two families of heuristics fundamentally differs; shallow learning demands much less attention than deep learning. One way to indicate that this additional recruited attention is a scare resource and not free is to impose a negative term or a cost term in the utility calculation. The cost depends on the amount of the information needing to be processed and the information-processing technology employed. The former is directly related to \( n \), whereas the latter is determined by the technology available to facilitate shallow and deep learning. By fixing \( n \), say \( n = 1 \), let us denote the unit cost of shallow learning (HBS) by \( c_H \) and that of deep learning (UBS) by \( c_U \). In a normal case, we may assume that \( c_U \geq c_H \), since the efforts required for the UBS are naturally greater than those required for the HBS; therefore, without losing generality, we assume that \( c_U = \alpha c_H \) (\( \alpha \geq 1 \)).\(^3\) The attention costs for the UBS(\( n \)) and HBS(\( n \)) are assumed to follow a simple linear form\(^4\) as \( C_U = nc_U \) and \( C_H = nc_H \), respectively.

In addition to the two data-driven decision heuristics, we also consider a kind of zero-intelligence agent (randomly-behaved agent), denoted by Random, who simply bases his/her decision on null information; in other words, \( n = 0 \).

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\(^2\) The reference point is determined as the expected value of the items so that the probability of the idle item being larger than the active item is less than the probability of the idle item being smaller than the active item. In this paper, the specific reference point which we employ is the average of \( EV_i \), i.e., 0.5.

\(^3\) It is possible that the constant progress in the information and communication technology may narrow the gap, and in the limit \( c_U = c_H \), and even \( c_U = c_H = 0 \). Our simulation, to be detailed in Section 2.4, will explore this rich combination.

\(^4\) The cost function can easily be extended to a nonlinear form which may depict the cost more accurately. However, in our paper, the purpose is to gain insight into how big data impacts the decision through reducing the attention cost but not the exact form of attention cost function. Hence, a simple linear function can serve better here.
This agent then randomly selects one of the two items by throwing a fair coin with no attention cost.

The above three types of strategies, namely, UBS\((n)\), HBS\((n)\), and Random, constitute the pool of strategies interesting us. Presumably, we can leave \(n\) as a free variable to choose, ranging from 1 to \(N - 1\), since its implied computational burden (cost) has become part of \(C_U\) and \(C_H\). We, nonetheless, further constrain this range up to \(K\) (\(K \leq N - 1\)) by recognizing the operational physical limit (a fatigue point). Therefore, effectively, the pool size of the available strategies is \(2K + 1\). In Table 1, we number these strategies from 1 to \(2K + 1\) by assigning the first \(K\) (1, 2, ..., \(K\)) to UBS\((n)\) strategies, the next \(K\) to HBS\((n)\) strategies (\(K + 1, ..., 2K\)), and the last one (2\(K + 1\)) to Random.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Labels and numbering of strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility-based strategies</td>
<td>Herd-based strategies</td>
</tr>
<tr>
<td>Label</td>
<td>Numbering</td>
</tr>
<tr>
<td>UBS1</td>
<td>No. 1</td>
</tr>
<tr>
<td>UBS2</td>
<td>No. 2</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>UBSK</td>
<td>No. (K)</td>
</tr>
</tbody>
</table>

In each period, the agent, based on his/her experience with these \(2K + 1\) strategies, will choose one for the purpose of information processing and decision making. This choice-making and experience-updating process is done through reinforcement learning, which is detailed in the next subsection.

2.3 Reinforcement learning

In this subsection, we introduce the learning behavior of agents. Recall that learning in our model proceeds at two levels: at the bottom level, it is social learning (learning from others), be it deep or shallow, whereas at the meta-level it is individual learning (learning how to learn from others), which is dictated by the repeated discrete choice over the aforementioned \(2K + 1\) strategies. In economics, the discrete choice problem is frequently solved with reinforcement learning, a learning procedure which is first introduced by psychologists.\(^5\) Reinforcement learning has a number of variants, and the one used in Vriend (2002) and Yu et al (2018) is known as the classifier-system algorithm, as introduced by Holland (1986), which is different from the famous Roth-Erev algorithms (Roth and Erev, 1995; Erev and Roth, 1998) frequently used in experimental economics. In this article, we adopt the former.

Despite their fine differences, all variants of reinforcement learning have two fundamental constituents, namely, a propensity (strength) updating scheme and strategy choice scheme. The former refers to how the propensity (strength, \(^5\) For a review of reinforcement learning and its use from psychology to economics, the interested reader is referred to Chen (2016).
score) of each strategy is updated, and the latter refers to the stochastic choice given the updated score of each strategy.

For each strategy \( k (k = 1, \ldots, 2K + 1) \), let \( s_{k,t} \) be the score (propensity) of the strategy in period \( t \). Then its update proceeds as follows:

\[
s_{k,t+1} = \begin{cases} 
  s_{k,t} + w(u_t - s_{k,t}), & \text{if } k \text{ is chosen at } t, \\
  s_{k,t}, & \text{otherwise.}
\end{cases}
\]  

(1)

By Equation (1), if the strategy \( k \) is chosen in period \( t \) and it is assumed that the item chosen, as suggested by strategy \( k \), leads to a consumption utility \( u_t \), then this utility will be attributed to the score updating of strategy \( k \) as shown in the first branch of Equation (1). However, if strategy \( k \) is idle (not chosen) in period \( t \), then its score remains the same, as shown in the second branch. Notice that the consumption utility \( u_t \) is actually the net consumption utility after taking into account the attention costs. To be precise, if we let \( v_t \) be the gross utility originally gained from the item chosen, then \( u_t = v_t - C_k \), whereas \( C_k \) is the attention cost evoked by strategy \( k \).

The first branch can also be rearranged as \( s_{k,t+1} = (1 - w)s_{k,t} + wu_t \), which makes it easier for us to see the role \( w \) being a weighted-average factor, assuming that \( 0 < w < 1 \). One can easily show that this updating scheme can be rewritten as the familiar exponentially weighted moving average of all \( u_{t'}, t' \leq t \) conditioned on \( k \) being activated. Hence, the score values range between 0 and 1, since the utility experienced from consuming an item ranges from 0 to 1 as indicated in Section 2.1.

The second constituent of reinforcement learning is the stochastic choice scheme. While reinforcement learning will lead agents to adopt those strategies which performed well in the past, it also allows those inferior ones some small chance of being chosen. With this consideration, a random perturbation will be first added to the score of each strategy,

\[
s'_{k,t+1} = s_{k,t+1} + \epsilon_{k,t+1}, \quad \epsilon_{k,t+1} \sim N(0, \sigma)
\]  

(2)

and each agent will then choose the strategy with the highest score:

\[
k^*_{t+1} = \arg \max \{ s'_{k,t+1} \}.
\]  

(3)

This finishes our reinforcement learning cycle for one individual agent. Notice that reinforcement learning is an individual form of learning, i.e., each agent learns from his/her own experiences of using these strategies. Having said that we assume that each agent maintains his/her own pool of strategies by updating the strength of his/her strategies individually.

2.4 Parameter settings and simulation procedure

In our simulation, we use the agent number \( N = 100 \), just as in Vriend (2002) and Yu et al (2018). The simulation period in one run is \( T = 1,000,000 \), which is different from Vriend (2002) and Yu et al (2018) where it is only
25,000 periods. This is because they are only concerned about the frequency of correct choices in each period, which becomes stable more quickly. In our model, however, we are more concerned about the attention level embedded in the strategies, which reach a statistically stable state (or quasi-equilibrium) much more slowly, as shown in the typical strategy dynamics in the top-left panel of Figure 2 below.

Since agents have limited attention in view of the huge amount of information available, the maximum number \(K\) of other agents that an agent can access for information is set to 20. Hence, there are in total \(2K + 1 = 41\) strategies (see Table 1) in the strategy pool of each agent, including 20 utility-based strategies, 20 herd-based strategies, and 1 random strategy. This upper bound of the agents’ attention level provides agents with enough flexibility in endogenous attention selections and ensures that the total number of strategies is not too large so that the simulation is feasible.

Table 2 Exogenous parameters in simulations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value range</th>
</tr>
</thead>
<tbody>
<tr>
<td>(N)</td>
<td>The number of agents</td>
<td>100</td>
</tr>
<tr>
<td>(T)</td>
<td>Periods in a simulation run</td>
<td>1000000</td>
</tr>
<tr>
<td>(K)</td>
<td>The maximum number of observations (maximum attention level)</td>
<td>20</td>
</tr>
<tr>
<td>(s_0)</td>
<td>The initial strategy score (same for all (2K + 1) strategies of all (N) agents)</td>
<td>0.5</td>
</tr>
<tr>
<td>(w)</td>
<td>The learning rate (i.e., the weight of current utility in strategy score updating)</td>
<td>0.025</td>
</tr>
<tr>
<td>(\sigma_\epsilon)</td>
<td>The standard deviation in the normal distribution (\epsilon \sim N(0, \sigma_\epsilon)) of the white noise of strategy score (i.e., trembling hand in strategy choice).</td>
<td>0.0025</td>
</tr>
<tr>
<td>(c_U)</td>
<td>The attention cost of one observation in a utility-based strategy.</td>
<td>0 to 0.012 with increment 0.0005, with typical value 0.005.</td>
</tr>
<tr>
<td>(c_H)</td>
<td>The attention cost of one observation in a herd-based strategy.</td>
<td>0 to (c_U) with increment 0.0005, with typical value 0.0025.</td>
</tr>
</tbody>
</table>

Agents will update the scores for their strategies to measure their fitness according to formula (1); in order to enable the learning process to start, the scores for each strategy must be initialized. We set the score for each strategy for any agent to 0.5. The initial value of the strategy score in Vriend (2002) is \(s_0 = 1\). We use \(s_0 = 0.5\) because the score ranges from 0 to 1 (as shown in section 2.3) and experiments show that this causes the society converge quickly to the stable state. The learning rate (i.e., the weight of the current utility in strategy score updating) is set to \(w = 0.025\) and the standard deviation of the white noise in the strategy score is set to \(\sigma_\epsilon = 0.0025\), with both following the setting of Vriend (2002).
The most important role of big data is to decrease the cost of seeking and processing information, which is reflected in the cost of attention paying to the information. In order to study the impact of big data on the quality of decision-making, we explore the combination of different cost parameters \(c_H\) and \(c_U\) for shallow (the herd-based strategy) and deep learning (the utility-based strategy), respectively. We perform the simulation with \(c_H\) ranging from 0 to 0.012 with increments of 0.0005; and for each \(c_H\), we conduct the simulation with \(c_U\) ranging from \(c_H\) to 0.012, with the increments of 0.0005. The shallow and deep learning costs cover all combinations from 0 to 0.012, keeping \(c_H \leq c_U\). We choose a maximum attention cost level of 0.012 because many agents will avoid paying attention to information for both shallow and deep processing and will choose to adopt free random strategy both near and above this cost level. All the exogenous parameters are listed in Table 2.

After the parameters are initialized, the simulation runs for \(T\) periods. For each period,

(i) the expected value \(EV_i\) \((i = 1, 2)\) for each of two items is generated from the uniform distribution \(U(0.25, 0.75)\);

(ii) the order of agents to make decisions is shuffled randomly;

(iii) for each agent in the queue, one strategy is selected with the highest score (plus a white noise \(\epsilon\)) to be applied in this period, where a choice is made according to the rule prescribed by the selected strategy, and the utility obtained is provided by the selected item as a random number from the uniform distribution \(U(EV_i - 0.25, EV_i + 0.25)\). The score for this strategy is updated according to formula (1);

(iv) the key variables are stored at the end of this period after all agents make choices, including the success ratio (which is the percentage of those agents who choose the superior item among all \(N\) agents), utility per capita (which is the average of the utility obtained by \(N\) agents in each period), strategy frequencies (one record for each strategy, which is the proportion of those agents who choose a certain strategy among all \(N\) agents), strategy utilities (one record for each strategy, which is the average utility of those agents who choose the strategy) and strategy scores (one record for each strategy, which is the average score of the strategy valued by all \(N\) agents).

Notice that everything is independent over different periods except for the strategy scores which measure the performance of the \(2K + 1\) strategies of each agent. Strategy scores are the only things that last from period to period through the learning process of agents. They determine the probabilities that the \(2K + 1\) strategies will be adopted and consequently the decision quality of the agents in the society. The pseudo-code for the simulation is provided by algorithm 1 in the Appendix.
3 Results and analysis

3.1 Typical simulation results

We first introduce the simulation results with a typical parameter setting in detail to provide a clear view of the model implications and then move on to the effect of attention scarcity in the next subsection. The parameter settings used here are $c_U = 0.005$ and $c_H = 0.0025$, with other parameters as given in Table 2.

Figure 1 shows the success ratio in a simulation run. The left panel is the time serial from period 1 to period 1,000,000 (with an interval of 100 periods for a clearer appearance). Looking horizontally, the most dense stripe of points concerns the success ratio from 0.8 to 0.95, which implies that in those periods, about 80% to 95% of the agents make the right choice. The average success ratio in all periods is about 0.65 and the median of the success ratios is over 0.78. Hence, the average success ratio is significantly larger than 0.5 which is the random choice with no information and learning. This is interpreted as the wisdom of crowds. However, the probability that most people make a wrong choice is also very large, and in about 18% of the periods that over 82% of the agents choose the inferior item. This is interpreted as the stupidity of herding. The probability distribution of the success ratios in the right panel verifies this result, with the highest peak at about 0.9 and the second highest peak at about 0.3. Both Vriend (2002) and Yu et al (2018) have presented similar results and Yu et al (2018) have provided a in-depth explanation of this phenomenon.
We are more concerned with the endogenous attention level in the information aggregation, which is embedded in the strategy dynamics in our model. The top-left panel of Figure 2 illustrates the evolution of strategy frequencies. We perform 10 runs of the simulation for the same parameter setting, and average the frequencies of 41 strategies in each period over 10 runs. All strategies start at a frequency of about 0.048 (1/21) because they have the same score at the beginning and have an equal chance of being adopted; according to the utility the strategies provide, some of them increase gradually, some of them remain at the same level, while others gradually decrease. We do not determine here which strategy one specific line represents, and only present a general idea that strategy frequencies are evolving over time. Notice that after about period 300,000, the strategy frequencies reach a statistically stable state, which is referred to as the quasi-equilibrium, when the strategy frequencies do not show any significant trends but fluctuate at certain levels. This is also the reason why we have to simulate for up to 1,000,000 periods to ensure that the society reaches the quasi-equilibrium. On the contrary, in Vriend (2002) a simulation runs for 25,000 periods because he is only concerned about the frequency of correct choices being stable. We replicate his simulation to find that 25,000 periods is also not enough for his strategies to be stable.

Table 3 Strategy frequency at the quasi-equilibrium in a typical simulation, averaged over 10 runs, listed in descending order by frequency. The red color for the herd-based strategies (HBS1 to HBS), the blue color for the utility-based strategies, and yellow for the random strategy. The last three underlined cells are for the total relative frequency of all utility-based strategies, herd-based strategies and the random strategy, respectively.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Frequency</th>
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<td>UBS1</td>
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</tbody>
</table>

Although we do not distinguish which strategy one specific line represents, we can see clearly that in the quasi-equilibrium two strategies are more frequently adopted than others, and three other strategies follow. All other lines seem to be winged together, but we can also notice that some of them are in general more frequent than others, forming different “layers” of strategies.
Big Data, Scarce Attention and Decision-Making Quality

Fig. 2 The strategy frequency and strategy score averaged in 10 runs with the typical simulation parameters $c_U = 0.005$ and $c_H = 0.0025$. Top-left panel is the average strategy frequency for 41 strategies. The top-right panel presents the average strategy scores for 41 strategies. The bottom-left panel includes the mean frequencies for the 41 strategies at the quasi-equilibrium (after 3,000,000 periods). The bottom-right panel contains the mean scores for the 41 strategies at the quasi-equilibrium. The red bars in the bottom two panels are for herd-based strategies, blue bars are for utility-based strategies, and the yellow bar is for the random strategy. The colors in the top two panels are for distinguishing different lines and there is no correspondence in color between the top two panels and bottom two panels.

The distribution of strategy frequencies at the quasi-equilibrium is clearly shown in the bottom-left panel of Figure 2. The horizontal axis represents the number of strategies, from 1 to 41. The 1st to the 20th strategies are utility-based strategies, UBS1 to UBS20, respectively; the 21st to the 40th strategies are herd-based strategies, HBS1 to HBS20, respectively; and the 41st strategy is the random strategy. The vertical axis depicts the relative frequency (probability) of each strategy adopted by all agents at the quasi-equilibrium (after 300,000 periods), averaged over 10 runs.

The two most frequently adopted strategies are HBS1 and HBS3, accounting for about 12.60% and 12.51%, respectively (see the list of strategies with their relative frequency in descending order in Table 3), and they correspond to the two lines for the strategy frequency dynamics at the top at the quasi-equilibrium (after about 300,000 periods) in the top-left panel. The 3rd to the 5th most frequently adopted strategies are also herd-based strategies, namely HBS2 (9.11%), HBS4 (8.71%), and HBS5 (7.18%), respectively. They are
significantly different from the top two (the small one with 12.51%) and the other following strategies (with the 6th largest one HBS6 being 4.64%), and hence they can be clearly distinguished as the three lines between the top two strategies and other winged ones in the top-left panel. Consistent between the bottom-left panel and the list in Table 3, we can see that the six strategies most frequently adopted are all herd-based strategies.

The most frequently used utility-based strategies, UBS6 (4.43%), UBS5 (4.43%) and UBS7 (4.29%) in turn, are ranked from the 7th to the 9th positions on the list. Combined with the 6th most frequent strategy HBS6 (4.64%), they comprise the first layer of the winged lines in the top-left panel. The rest of the strategies (lines) are divided into two layers, from UBS4 to UBS10 in Table 3 which is the second layer, and from HBS9 to UBS20 which is the third layer of the winged lines.

According to the model, an agent tends to employ the strategy with the highest score in his/her strategy pool. Hence, the strategy frequency dynamics and the strategy distribution at the quasi-equilibrium are actually determined by the dynamics and distribution of the strategy scores. This relationship is indicated by the two right panels of Figure 2. The top-right panel is the evolution of the average scores of 41 strategies. For one simulation run, the scores for each of the 41 strategies are averaged over 100 agents in each period to comprise 41 time serials. Then each of the 41 time serials are averaged period by period over 10 runs. We can see that the scores of all strategies start at 0.5 because they are initialized as such by all agents at the beginning of a simulation. It may seem surprising that the scores of all strategies drop dramatically after about the first 200,000 periods, considering that the score that an agent assigns to a strategy is the weighted average of utilities that the agent experienced from adopting the strategy and the expected utilities from some strategies (at least the random strategy) are no less than 0.5. The reason for this puzzle is that each agent is learning to use the most profitable strategies from his/her own experience, and some “potentially profitable” strategies may be abandoned with low scores by some agents only because of the “bad luck” as a result of producing less utility in the first few periods and rarely being used again, and different agents adapting to use different strategies with high scores in their own strategy pools. The strategy scores shown in the figure are averaged over all agents, and hence can be less than the expected utility provided in one application. After about 400,000 periods, the two strategies with the highest scores (HBS1 and HBS3) stop dropping and are maintained at a relatively stable level. After about 600,000 periods, the following three strategies with the highest scores (HBS2, HBS4 and HBS5) reach a stable level. Furthermore, the lines for the average scores of other strategies are winged together (as in the top-left panel) and seem to keep decreasing gradually throughout the simulation. From the point of view of the strategy score dynamics, the system does not reach a quasi-equilibrium even after an evolution of as many

---

6 We cannot and do not attempt to identify the border between layers. However, some white blanks are faintly visible between them. A simple one-dimensional k-mean clustering algorithm (Hartigan and Wong, 1979) provides the same partition.
as 1,000,000 periods. Because we are mainly concerned with the strategy dynamics and the embedded endogenous attention level, the quasi-equilibrium in the strategy dynamics is enough for our analysis. The causal relationship between the strategy score and strategy frequency can be better illustrated by the shape of the average scores for 41 strategies at the quasi-equilibrium shown in the bottom-right panel of Figure 2, which is almost exactly the same shape as the strategy frequency distribution in the bottom-left panel, and the correlation coefficient between the 41 strategy frequencies and 41 strategy scores is calculated to be 0.9997 with an extremely small p-value of $4.0282 \times 10^{-65}$.

An interesting result is that the attention level (number of observations $n$) employed by the utility-based strategy adopters and herd-based strategy adopters is very differently distributed, as shown in the bottom-left panel in Figure 2. Recall that the horizontal axis is the number of the strategies; at the same time, it also indicates the attention level ($n$) of the strategies, that is, the number of observations of utility-based strategy No. 1 to strategy No. 20 is 1 to 20, respectively, and the number of observations of herd-based strategy No. 21 to strategy No. 40 is 1 to 20, respectively (see Table 1 for reference with $K = 20$).

![Fig. 3 Attention distribution of utility-based strategy (UBS) adopters and herd-based strategy (HBS) adopters. The fitted lines are the probability density functions of Gamma distributions with parameters $k = 4.71, \theta = 1.51$ for the utility-based strategy and $k = 2.00, \theta = 2.08$ for the herd-based strategy.](image)

The largest proportion of the utility-based strategy adopters observe the choices and experienced utilities of 6 or 5 other agents before making decisions. As we know, the frequency of a strategy is determined by the score which is the weighted average of the score for that strategy. Hence, the optimal attention level for the utility-based strategy is about 5 or 6. Furthermore, the profitability of the utility-based strategy decreases if the agent attends to the information from either more or less of the other agents.

On the contrary, the largest proportion of the herd-based strategy adopters observe 1 or 3 other agents. Furthermore, in general, the frequency of the herd-based strategies decreases with the attention level $n$, except for number of observations 2. In particular, the frequency drops quickly as the attention level begins to increase (from 4 to 10 roughly). This indicates that the best choice for the herd-based strategy adopters is to observe only a few other
agents, and the more that are observed, the less utility that is expected. The frequency or the expected utility of HBS2 is obviously less than that of HBS1 and HBS3, and this is easy to understand recalling that an agent will randomly select one of the two items if the degree of popularity of both items is the same in his/her observation sample.

We attribute the difference in the attention distribution between two families of strategies to the marginal utility that an observation can contribute to different strategies. The utility-based strategy adopters observe the choices and utilities experienced by $n$ other agents and select items with higher average utility; the herd-based strategy adopters observe the choices of other agents and follow the majority. Hence, in general, an additional observation is more important for utility-based strategies than herd-based strategies. Because we use a linear attention cost function for both families of strategies, the marginal utility is mainly determined by the potential increase in the probability that an agent can make the right choice due to observing the information from one more other agent. For herd-based strategies, the function of an additional observation is either to confirm the popularity of an item or (badly) to confuse the popularity. Hence, an additional observation provides less marginal utility, and the marginal utility of an observation is decreasing dramatically as the number observations exceeds 3. For the utility-based strategies, because agents need to compare the average utilities of two items, an additional observation contributes substantial information; in particular, when there is only a little information, the additional observation is relatively more important and provides a higher marginal utility. As the number of observations increases, the marginal utility becomes less and less. Due to the linear cost function, the number of observations reaches the optimal level (about 5 to 6 in our typical simulation) when the marginal utility is below the unit attention cost.

The attention (number of observations) distribution of both utility-based strategy adopters and herd-based strategy adopters can be well fitted by the Gamma distributions (Hogg and Craig, 1995) as shown in Figure 3. The attention level of the utility-based strategy follows $n_U \sim \Gamma (k, \theta) = \Gamma(4.71, 1.51)$ and that of the herd-based strategy follows $n_H \sim \Gamma(2.00, 2.08)$. The shape parameter $k$ of a Gamma distribution determines its skewness $skew = \frac{2}{\sqrt{k}}$ and kurtosis $kurt = \frac{6}{k}$. Hence, the smaller the shape parameter $k$, the more right-skewed or the longer the tail on the right-hand side of the distribution; and the smaller the shape parameter $k$, the higher the peak, more rapid the decay, and the heavier the tails of the distribution. The Gamma distribution becomes an exponential distribution if $k = 1$, and approaches a normal distribution when $k$ is large (approximately when $k > 10$). So, as observed previously, the attention distribution of the herd-based strategy is more skewed and has a higher peak than that of the utility-based strategy. $\bar{n}_U = k\theta = 7.0882 \quad \bar{n}_H = k\theta = 4.1671 \quad skew = \frac{2}{\sqrt{k}} = 0.9219 \quad kurtosis = \frac{6}{k} = 1.2748$

It may seem that the attention distribution for the herd-based strategy follows an exponential distribution, but we tried both the gamma and exponential distributions and found that the former fits better.
We then compare the total frequency, average expected utility and average attention level (number of observations) of two families of strategies, treating each family of strategies as a whole, as shown in Figure 4.

Fig. 4 The frequency, number of observations and utility of two families of strategies, i.e., the utility-based strategy and the herd-based strategy, averaged over 10 runs with typical simulation parameters \( c_U = 0.005 \) and \( c_H = 0.0025 \).

The top-left panel is the total frequency dynamics of the utility-based strategies and herd-based strategies, which can be obtained by summing up the frequencies of the No. 1 to No. 20 strategies and No. 21 to No. 40 strategies respectively in the top-left panel of Figure 2 period by period. Both frequencies of the two families of strategies start at about 0.4878 (20/41) because all 41 strategies are assigned an initial score of 0.5 by all agents and have the same chance of being employed. The total frequency of all utility-based strategies decreases rapidly and, at the same time, the frequency of all herd-based strategies increases rapidly. The total frequency of all utility-based strategies decreases rapidly, at the same time, the frequency of all herd-based strategies increases rapidly. The frequencies of the two families of strategies reach the quasi-equilibrium (relatively stable state) very quickly at about 200,000 periods (much more quickly than that of individual strategies). At the quasi-equilibrium, more agents adopt herd-based strategies (about 66.21%) than
those adopting utility-based strategies (about 33.41%). This result is consistent with the numbers in Table 3 and the bottom-left panel in Figure 2.

The dynamics of the number of observations are shown in the bottom-left panel. The blue line is the average number of observations of all agents adopting utility-based strategies in each period. This can be calculated as the weighted average of the number of observations 1 to 20 using the weight as the relative frequency (percentage) of agents adopting the corresponding strategy. Similarly, the average number of observations of herd-based strategies can be calculated and represented by the red line. Both lines start at about observation number 10 at the beginning, because all strategies are initialized to have an equal chance of being selected. The number of observations of both families of strategies drop rapidly during the first 100,000 periods and reach the quasi-equilibrium with average number of observations about 7.11 and 4.16 for the utility-based strategies and herd-based strategies, respectively. The black line is for the average number of observations for all strategies, which also starts from 10 and drops to about 6.10 at the quasi-equilibrium. This number is also the average observation of utility- and herd-based strategies weighted by their frequency, for example, the average number of observations at the quasi-equilibrium 6.10 is the average of 7.11 and 4.16 weighted by 66.21% and 33.41%. From the two left panels we can see that more agents adopt herd-based strategies than utility-based strategies and the herd-based strategy adopters observe fewer other agents for information than the utility-based strategy adopters.

The top-right panel is the utility per capita for agents adopting utility-based strategies (blue line) and herd-based strategies (red line). For each period, we sum up the utilities of all agents employing utility- or herd-based strategies and then divide the sum by the number of agents employing this family of strategies to obtain the utility per capita for the two families of strategies. The utility per capita of both families of strategies increases in the learning process of agents and reaches a quasi-equilibrium with relatively stable utilities of about 0.5112 (utility-based strategies) and 0.587 (herd-based strategies). It is surprising that the two families of strategies persistently provide different levels of utilities, which runs counter to the common knowledge in replicator dynamics that all surviving strategies provide the same expected utility. After deliberate investigation and thinking, we find that this difference comes from the learning mechanism in our model and replicator dynamics. Replicator dynamics is essentially a mechanism of social learning, the basic idea of which is that agents compare their utility with that of other agents and learn to use the more promising one. The learning mechanism used in our model as elaborated in Section 2.3 is essentially individual learning, whose basic idea is that the agents update their strategies according to their own experience in history. Because the utility of herd-based strategies is higher than that of utility-based strategies, then a higher proportion of UBS agents may learn to switch to herd-based strategies and there is also a lower proportion of the agents switching in the opposite direction. Considering that the frequency of the HBS agents is higher than that of the UBS agents (see the top-left
In this subsection, we provide the simulation results with the typical parameter settings to reveal how the attention scarcity affects the endogenous number of observations of agents with two families of decision heuristics in a sequential decision-making situation. We find that more agents adapt to employ shallow learning (herd-based strategies) than deep learning (utility-based strategies), and shallow learning agents tend to observe less information and enjoy higher expected utilities than deep learning agents. How the big data, through the way of reducing the cost of two families of learning, affects the decision heuristics and the attention level of agents will be investigated in the next subsection.

3.2 Big data effect on endogenous attention and decision-making quality

We try to answer the question as to whether big data makes the attention ‘richer’ or ‘scarcer’ and the decision-making quality ‘better’ or ‘poorer’ in this subsection. Big data have a great impact on the social decision making. As a new type of “information processing system”, the main function of big data is “attention-conserving” (Simon, 1971, p.43, italics added) by “organizes information and compresses it” (Simon, 1968, p.623, italics added). While the scarcity of attention is modeled in this paper by the cost function for seeking and processing information, then, the attention-conserving function of big data can be reflected by the reduction in the attention cost. Hence, by investigating the effect of attention cost on the individuals’ decision heuristics and decision-making quality, we can have the effect of the big data on them.

![Diagram](image)

Fig. 5 The effect of attention cost on decision-making quality in 3D plot.
Figure 5 illustrates the impact of attention cost on the decision-making quality. We distinguish the cost required by two different families of decision heuristics, i.e., the shallow learning (herd-based strategies) and deep learning (utility-based strategies). As pointed out in Section 2.2, the unit cost of seeking and processing a piece of information using shallow learning is usually less than that of using deep learning. The two axes in the horizontal plane in the left panel of Figure 5 are the unit attention cost of the utility-based strategy (UBS) and herd-based strategy (HBS), i.e. $c_U$ and $c_H$ as defined in Section 2.2. The value range of $c_U$ is from 0 to 0.012. Given each $c_U$, the value of $c_H$ ranges from 0 to $c_U$. The vertical axis is the utility per capita at the quasi-equilibrium, which is the average utility of all agents in all $[T/3]$ to $T$ periods of a simulation. Hence, it is an indicator for the social welfare.

From this figure, we can see that the social welfare (utility per capita at the quasi-equilibrium) depends mainly upon the unit cost of the UBS ($c_U$). There is a significant correlation between $c_U$ and the utility per capita. Intuitively, the smaller the UBS unit cost, the higher the social welfare. The correlation coefficient between $c_U$ and the utility per capita is calculated as -0.8878 with an extremely small $p$-value of $6.7659 \times 10^{-111}$. This implies that if big data can reduce the unit attention cost required by the utility-based strategies, the social welfare can be improved significantly.

The relationship between the unit attention cost of the HBS ($c_H$) and the social welfare is relatively weak and somewhat confusing. The correlation coefficient between them is calculated as -0.2202 with a $p$-value of $6.274 \times 10^{-5}$. This seems to indicate that the HBS attention cost is negatively related to the utility per capita in equilibrium and reducing the HBS attention cost can improve social welfare. However, it should be noticed that the values of $c_H$ and $c_U$ are not completely independent, as we assume that $c_H \leq c_U$. So the correlation between the small HBS attention cost and the higher social welfare may be the result of the small UBS attention bound with the small HBS cost.

In order to identify the effect of the HBS attention cost on social welfare, we fix the UBS cost ($c_U$) at 0.005 and 0.01 and vary only the HBS cost ($c_H$). We thereby obtain two curves (black) on the surface of the utility function. These two curves are drawn in 2D planes in the two right panels, which clearly show that the utility per capita (social welfare) generally decreases when the HBS cost is reduced (read along the axis from right to left). We have an interesting results in that if the big data can only reduce the attention cost of shallow information but not the deep information, the decision-making quality is not improved but is instead impaired.

A multiple quadratic regression is applied to further investigate the effect of the attention cost of two behavioral heuristics on social welfare. The dependent variable is the utility per capita ($utility\text{-}per\text{-}capita$), and the independent variables are the unit attention cost $c_H$, $c_U$ and their quadratic terms. The regression equation is,

\[
utility\text{-}per\text{-}capita = \beta_0 + \beta_1 c_U + \beta_2 c_H + \beta_3 c_U^2 + \beta_4 c_U c_H + \beta_5 c_H^2 + \epsilon \quad (4)
\]
The regression results are summarized in Table 4. The quadratic model fits the data very well, as the adjusted $R^2 = 99.1\%$, indicating that the estimated quadratic equation of $c_U$ and $c_H$ can explain almost all the variance of the dependent variable, i.e. the utility per capita. The p-values of the coefficients for $c_U$, $c_H$, $c_U^2$, and $c_H^2$ are extremely small which suggests that these coefficients are significantly different from zero and that the changes in these terms will lead to changes in the utility per capita.

<table>
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</table>

* Number of observations 325, Adjusted $R^2 = 0.991$.

The coefficients themselves cannot directly reflect the importance of the independent variables to the dependent variable, because the independent variables are measured in different unit scales. In order to identify which of the two types of attention cost (UBS attention cost $c_U$ and HBS attention cost $c_H$) has a greater effect on the social welfare (utility per capita), the standardized coefficients (Freedman, 2009) are also calculated by normalizing all the dependent and independent variables to have a mean of 0 and standard deviation of 1. The standardized coefficients represent how many standard deviations a dependent variable will change in response to a one standard deviation increase in the dependent variable. The terms $c_U$ and $c_U^2$ in the regression equation have the largest and the second largest absolute values of standardized coefficient, with $\beta_1 = -2.2442$ and $\beta_3 = 1.2878$. This indicates that the attention cost for the utility-based strategy which involves the deep information processing $c_U$ has a more important effect on the average utility of social members. The coefficient for the first-order term $c_U$ is negative, i.e., $\beta_1 < 0$, which is consistent with the results observed in Figure 5 in that the reduction in the UBS attention cost can improve social welfare. The coefficient for the second-order term $c_U^2$, is positive, i.e., $\beta_3 > 0$, which implies that the rate of social welfare improvement is increasing as $c_U$ becomes smaller, which can also be observed in the left panel of Figure 5.

The terms $c_H$ and $c_H^2$ have relatively smaller values of the standardized coefficient, with $\beta_2 = 0.7138$ and $\beta_5 = -0.3612$. This indicates that the attention cost for the herd-based strategy which only involves shallow information processing $c_H$ has a less important effect on the social welfare. The coefficient for the first-order term $c_H$ is positive, i.e., $\beta_2 > 0$, which is consistent with the results shown in the right two panels of Figure 5 in that the reduction in
the HBS attention cost will impair the social welfare. The coefficient for the second-order term $c_H^2$ is negative, i.e., $\beta_5 < 0$, which implies that the rate of social welfare reduction is increasing as $c_H$ becomes smaller, which can also be observed in the right two panels of Figure 5.

![Fig. 6 Strategy frequency distributions with different HBS cost ($c_H$), and the UBS cost ($c_U$) fixed at 0.005.](image)

![Fig. 7 Strategy frequency and number of observations with different HBS cost ($c_H$), and the UBS cost ($c_U$) fixed at 0.005.](image)

It is easy to understand that the smaller UBS attention cost leads to higher social welfare because more agents will learn to choose UBS strategies and obtain more deep information about the choices and resultant utilizes by other agents, and with more information agents can make more accurate decisions. However, it is very counter-intuitive that the unit cost of HBS ($c_H$) is positively
related to the social welfare, which implies that the reduction in the HBS cost impairs the social welfare. In order to understand this phenomenon, we further investigate how the HBS cost influences the decision heuristics of agents with the UBS cost fixed. Figure 6 presents some strategy frequency distributions similar to the bottom-left panel of Figure 2 with the HBS cost \(c_H\) ranging from 0 to 0.005 and the UBS cost \(c_U\) fixed at 0.005, corresponding to the top-right panel of Figure 5. We can see that as the HBS cost decreases, more and more agents adopt herd-based strategies, and less and less agents adopt utility-based strategies (more clearly shown in the left panel of Figure 7); at the same time, the number of observations of herd-based strategies is slightly increasing and that of the utility-based strategies is dramatically decreasing (more clearly shown the right panel of Figure 7). Recalling two families of decision heuristics, utility-based strategy adopters compare the realized utilities of two items to make choices, while the herd-based strategy adopters only follow the majority choice. Hence, for the whole of the society, only the utility-based strategies provide really useful information. So, the reduction in the HBS cost induces more agents to adopt herd-based strategies based on their own utility-maximization incentives, and this leads to the collective irrationality that the social welfare decreases.

![Strategy frequency distributions](image)

**Fig. 8** Strategy frequency distributions with different HBS cost \(c_H\), and the UBS cost \(c_U\) fixed at 0.01.

Figure 8 presents the strategy frequency distributions with the HBS cost \(c_H\) ranging from 0 to 0.01 and the UBS cost \(c_U\) fixed at 0.01, corresponding to the bottom-right panel of Figure 5. With the same logic as the above, in a general sense, the social welfare becomes less and less as herd-based strategies becomes more and more popular with the reduction in the HBS cost. One
special point in the bottom-right panel of Figure 5 is that the utility switches from decreasing to increasing when the HBS cost becomes very close to zero, which can also be shown by the small ‘valley’ in the lower left corner of the 3D plot in the left panel of Figure 5. From the strategy frequency distributions in Figure 8, we can see that when the HBS cost decreases from 0.01 to 0.002, the frequency of the random strategy (No. 41) is increasing. This is because the social average utility is decreasing, and due to the stochastic characteristic in the learning process, the chance of the random strategy being selected increases (as shown in the left panel of Figure 9); at the same time, the number of observations of herd-based strategies is increasing and that of the utility-based strategies is decreasing (as shown in the right panel of Figure 9). Notice that, when the HBS cost is less than 0.0003, the social average utility is less than 0.5 (the expected utility from the zero cost random strategy). Also due to the stochastic characteristic of the learning process, the strategies providing less than the 0.5 utility (as from the random strategy) still have a chance of being selected. When the HBS cost is reduced to 0, very few utility-based strategies are adopted, and only the herd-based strategies and a small proportion of the random strategy are adopted, and hence the social average utility recovers to 0.5, the expected utility from the zero-cost random strategy, as shown in the bottom-right panel in Figure 5.

In this subsection, we study the effect of big data upon the individual heuristics and the resulting society-level decision quality through the lens of attention cost. If big data technology reduces the attention cost to the deep information, more individuals will adopt utility-based strategies (deep learning), and the society-level decision quality will be improved. However, if the big data technology only reduces the attention cost to the shallow information but not that to the deep information, more individuals will adopt herd-based strategies (shallow learning), the information available will not be sufficiently exploited, and the society-level decision quality will diminish.
4 Discussion and Conclusion

In order to study how the big data changes the individual behaviors and the society-level decision quality, we explicitly model the simultaneous and endogenous choice of attention level and decision heuristics in the information aggregation of a sequential decision process. In a society with population interconnected by social networks, information is scattered all over among the individuals. To make a decision, an individual needs to aggregate the fragments of information obtained from others.

Due to the scarcity of attention (Simon, 1971), attention is costly, which means that to seek and process a piece of information implies a loss of utility on the part of this individual and this utility loss may result from the time and effort paid to this information or there may be an opportunity for a utility gain if this attention is directed towards another task. As the information content increases in terms of abundance and availability, attention, the focused mental engagement on information, becomes the limiting factor in the processing of information (Davenport and Beck, 2013).

Modeling behavior when information gathering and processing is costly has been central to economic analysis since the seminal work of Stigler (1961). The rational inattention framework, first proposed by Christopher Sims (Sims, 2003, 2006), allows the agent to optimally allocate his or her pool of attention thus giving control over not only when, but also how much, attention is paid (Lewis, 2009). Agents may selectively process information that they find useful and ignore information that is not worth the effort to acquire and process (Matejka and McKay, 2015). Rational inattention has been applied to macroeconomic dynamics (Luo and Young, 2009), monetary policy (Mackowiak and Wiederholt, 2009; Pasten and Schoenle, 2016), forward guidance policy (Gaballo, 2016), financial market (Abel et al, 2013), marketing (Tutino, 2013; Grubb, 2015), organization communication (Dessein et al, 2016), human resource management (Habermalz, 2014), and sequential decision making (Song, 2016), etc.

We are concerned about the society-wide level effect of big data on the information aggregation and decision-making quality. Although big data is widely believed to be a promising way to improve decision-making (Surowiecki, 2004), some warnings are also heard about it such as herding behavior (Bonabeau, 2004) and shallow thinking (Carr, 2011) which may erode the decision-making quality.

Simon highly emphasized the importance of decision making for the whole of society. He said “nothing is more important for the well-being of society than that this work [decision making] be performed effectively” and “(t)here are no more promising or important targets for basic scientific research than understanding how human minds, with and without the help of computers, solve problems and make decisions effectively, and improving our problem-solving and decision-making capabilities” (Simon et al, 1987). Just as Simon et al (1987) pointed out, “Human minds with computers to aid them are our
principal productive resource. Understanding how that resource operates is the main road open to us for becoming a more productive society”.

The function of big data, as an information processing system, lies in reducing the cost to individuals of the attention paid to information (Simon, 1971). We distinguish the attention costs required in two families of strategies, the utility-based strategies (deep learning) and the herd-based strategies (shallow learning). An agent who adopts a herd-based strategy observes what other agents did and follows the majority’s action, so he only needs information about the actions of others. A utility-based strategy adopter makes decisions based on the information of both the actions of other agents and the utilities from their actions. Intuitively, the attention cost for information required by deep learning is no less than that of shallow learning. As the big data technology has a role to play in reducing the attention cost, the effectiveness of the cost reduction for two families of strategies is different. To gather and organize the information regarding what other individuals did is relatively easy compared to that for the utility from other individuals’ actions. We study how the attention cost affects individuals’ information seeking and processing behavior (that is, how much information and what types of information will be used) and consequently society’s overall decision-making quality in this paper.

By simulation with the typical parameter settings, we find that more individuals employ shallow learning (herd-based strategies) than deep learning (utility-based strategies). Both families of strategies only attend to a limited number of rich available information, but the attention level employed by two families of strategies is very differently distributed. The optimal choice for the utility-based strategy is a moderate attention level, while the optimal choice for the herd-based strategy is to attend to only very little information. We attribute the difference in the attention distribution between the two families of strategies to the marginal utility that an observation can contribute. For the utility-based strategies, because agents need to compare the average utilities of two items, an additional observation contributes substantial information, especially when there is only little information. For herd-based strategies, the function of an additional observation is either to confirm the popularity of an item or (badly) to confuse the popularity. Moreover, we find that shallow learning agents enjoy higher expected utilities than deep learning agents. So a higher proportion of UBS agents switch from utility-based strategies to herd-based strategies than in the opposite direction. A dynamic equilibrium can be achieved considering that there are more herd-based strategy adopters than utility-based strategy adopters.

We find that the decrease in the information cost due to big data can encourage individuals to make use of more information, resulting in a better overall decision quality. However, if the big data only reduces the cost of shallow information but not that of deep information, the decision quality is diminished because more individuals are induced to adopt the herd-based strategy. This research provides reasonable explanations for the shallow information and shallow thinking bandsprading on the Internet. There are many indications that online behavior may be becoming more herdlike (Ommela and
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Reed-Tsochas, 2010; Sparrow et al, 2011; Bentley et al, 2014). With the situation of information overload (Hemp, 2009), crucial human decision making might be becoming more herdlike in contexts such as voting (Arawatari, 2009), mating (Lenton et al, 2008), music (Salganik et al, 2006), finances (Allen and Wilson, 2003), and public health (Bates et al, 2006). This result also proposes the implication that the key challenge of big data is to develop techniques to reduce the cost of deep information processing.

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Appendix: Pseudo-code of the simulation

See Algorithm 1.

References

Carr N (2011) The shallows: What the Internet is doing to our brains. W. W. Norton & Company
Algorithm 1: Pseudo-code of the simulation

1. for all $N$ players do
2.   strategy-score ← 0.5;
3. end
4. for $T$ periods do
5.   draw $EV_1$ and $EV_2$ independently from uniform distribution $U(0.25, 0.75)$;
6.   put all $N$ players in random order;
7.   for $N$ players in the generated random order do
8.     strategy-score-with-noise ← strategy-score + $\epsilon$, where $\epsilon \sim N(0, \sigma)$;
9.     chosen-strategy-no ← strategy with the highest strategy-score-with-noise;
10.    if $1 \leq$ chosen-strategy-no $\leq 20$ then
11.       to-observe-number ← chosen-strategy-no;
12.       if to-observe-number $\leq$ the number of agents who made choice before this agent then
13.          sample ← to-observe-number randomly chosen earlier actors;
14.       else
15.          sample ← all earlier actors;
16.       end
17.       calculate the average-utility of items 1 and 2 selected by sample, 0.5 if one item does not occur in sample;
18.       if average-utility of two items not equal then
19.          selected-item ← the item with higher average-utility;
20.       else
21.          selected-item ← randomly chosen one from two items, each with equal probability;
22.       end
23.       observation-number ← size of the sample;
24.       gross-utility ← random value from uniform distribution $U(EV_{selected-item} - 0.25, EV_{selected-item} + 0.25)$;
25.       utility ← gross-utility − observation-number · $c_U$ ($c_U$ is the attention cost for each piece of information for the utility-based strategy);
26. else if $21 \leq$ chosen-strategy-no $\leq 40$ then
27.       to-observe-number ← chosen-strategy-no − 20;
28.       if to-observe-number $\leq$ the number of agents who made choice before this agent then
29.          sample ← to-observe-number randomly chosen earlier actors;
30.       else
31.          sample ← all earlier actors;
32.       end
33.       count the selected-times of items 1 and 2 selected by sample;
34.       if selected-times of two items not equal then
35.          selected-item ← the item with higher selected-times;
36.       else
37.          selected-item ← randomly chosen one from two items with equal probability;
38.       end
39.       observation-number ← size of the sample;
40.       gross-utility ← random value from uniform distribution $U(EV_{selected-item} - 0.25, EV_{selected-item} + 0.25)$;
41.       utility ← gross-utility − observation-number · $c_H$ ($c_H$ is the attention cost for each piece of information for the herd-based strategy);
42. else if chosen-strategy-no $= 41$ then
43.       selected-item ← randomly chosen one from two items with equal probability;
44.       utility ← random value from uniform distribution $U(EV_{selected-item} - 0.25, EV_{selected-item} + 0.25)$;
45. end
46.   strategy-score ← (1 − $w$) · strategy-score + $w$ · utility;
47. end
48. save data for this period;
49. end