

## Critical Optimism: A Methodological Posture to Shape the Future of Digital Social Research

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### **How to cite**

Amaturò, E., Aragona, B. (2021). Critical Optimism: A Methodological Posture to Shape the Future of Digital Social Research. [Italian Sociological Review, 11 (4S), 167-182]

Retrieved from [<http://dx.doi.org/10.13136/isr.v11i4S.429>]

[DOI: 10.13136/isr.v11i4S.429]

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### **3. Article accepted for publication**

Date: January 2021

Additional information about  
**Italian Sociological Review**  
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# *Critical Optimism: A Methodological Posture to Shape the Future of Digital Social Research*

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## **Abstract**

In this paper we focus on the concept of critical optimism, a concept that has served many authors to explain orientation about the future. It means to be neither mechanistic in our imagination of the world nor naïve about the expectations the future can hold. Recently scholars have appealed to critical optimism to explain how we should relate to the digital, since when facing technology often, also in the scientific literature, we find extreme opinions. After ten years that the debate around technology and social research has developed on these two opposite visions, we promote an active engagement in testing the different instruments of digital research. Digital methods and big data must be integrated with traditional data sources and methods already existing in social sciences, and that is the right way to effectively improve the unfolding of social phenomena. In support of this thesis, we want to bring two examples that can demonstrate how the use of digital technologies did not lead to abandoning the traditional techniques of social research, but it instead has contributed to solving some problems in the use of these techniques, which before digital were hard to solve. Here, we will illustrate just two examples, the survey and the experiment, that relate to quantitative research, although certainly there are others that can be retraced in quantitative as well as qualitative research.

Keywords: critical optimism, digital survey, digital experiment.

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## 1. Introduction

People are often on the extreme ends when facing challenges. In this paper we focus on the concept of critical optimism, a concept that has served many authors to explain orientation about the future. It means to be neither mechanistic in our imagination of the world nor naïve about the expectations the future can hold. The concept has been employed in several disciplines ranging from pedagogy (Freire, 1996) to art history and computer engineer (Brueckner, 2018).

Recently, scholars have appealed to critical optimism to explain how we should relate to the digital, since when facing technology often, also in the scientific literature, we find extreme opinions, that vary from a blind faith in the opportunities opened by the new computational tools to the conviction that “everything is a disaster”, or, in other words, that social research is condemned.

In our opinion, this opposition recalls the opposition between *Apocalyptic* and *Integrated* that Eco (1964) expressed to explain the different postures we can have about popular culture. In effect, since recently the debate between scholars about the future of the digital in research methods has developed around oppositions, and big data, computation, and digital methods have been a contested epistemological terrain.

In this controversy we have had two groups, with different postures on the matter. On one side, those who were generally more optimistic, on the other side, those who were generally more critical (Salganik, 2018). Optimists believe the digital transform in better both the sciences and the methods once consolidated within the different scientific disciplines (Lazer et al., 2009; Mayer-Schonberger, Cuckier, 2012. Critics believe that digital methods and big data impoverish social sciences and their method (Boyd, Crawford, 2012), becoming a threat to the empirical sociology based on surveys and interviewing (Savage, Burrows, 2007).

Most of the discussion is about the role of technology. The optimistic scholars are enthusiastic about the possibilities opened by digital technology, while the critic ones contrast the adoption of such a tool. Optimists believe that technology is the driver of innovation and of advances in knowledge. This technological determinism promotes an idea in which the scientific disciplines stand at the passive end (Marres, 2017), with technology being a force of improvement for research. On the other hand, critics believe that the reconfigurability of digital infrastructures and devices is contested and it needs continue demonstration.

After ten years that the debate around technology and social research has developed on these two opposite visions, a large group of scholars, nowadays, supports an active commitment by social scientists to face the technological

dimension of social inquiry (Orton-Johnson, Prior, 2013; Lupton, 2015; Daniels, Gregory, Mc Millan Cottom, 2016). These scholars, in order to avoid ideological positions about the role of digital methods in social research, promote an active engagement in testing the different instruments of digital research, such as big data, machine learning, platforms analysis, search as research tools, and so on. They advocate that digital methods and big data must be integrated with traditional data sources and methods already existing in social sciences, and that is the right way to effectively improve the unfolding of social phenomena.

In support of this thesis, which we fully share, it is possible to bring numerous examples that can demonstrate how the use of digital technologies did not lead to abandoning the traditional techniques of social research, but it instead has contributed to solving some problems in the use of these techniques, which before digital were hard to solve. Here, for the sake of brevity, we will illustrate just two examples that relate to quantitative research, the survey and the experiment, although certainly there are as many others that can be retraced in qualitative research, for example in the ethnographic approach (Caliandro, 2018).

## **2. The third era of survey research**

Survey research began in the 1930s and since then three different periods have occurred in which both the way of administering the questionnaires and the procedures for extracting the cases to be interviewed have changed (Groves, 2011). Oversimplifying, in the first era the survey was done with face-to-face interviews with probabilistic samples extracted from local population lists. The second era of the survey is represented by the telephone interview with random sampling on entire national telephone directories. The third era of the survey instead sees the use of digital devices and computers with samples often extracted with non-probabilistic procedures and linked to big data sources.

A starting point for understanding the type of opportunity that digital opens up to survey research is the total survey error approach (Groves, Lyberg, 2010), which encodes the overall model of the errors that can be committed in the survey, and identifies two main sources of error: selection errors and measurement errors. The digital can intervene to help smoothing the difficulties on both of them. As it is widely known, among the selection errors there are three types of errors: the sampling error, the coverage error and the non-response error. The sampling error consists of the difference between the estimate and the real unknown parameter. When using probabilistic samples it is possible to estimate this error, since some parameters of the population are

known. In this case it will be possible to evaluate the goodness of the sample used and define its representativeness. The representativeness of a sample depends on the randomness with which it is constructed. On the contrary, when the sampling is a non-probabilistic one, it is only possible to approximate the effect that the choice of sample has on the research results. The coverage errors can be of two types: under-coverage and over-coverage. Under-coverage refers to those units which should be included in the actual sample, but which in practice do not appear. In the past, these errors were generally caused by delays in registering births or transfers in the registry office records or by users who did not have a telephone, or by the choice of not being listed in telephone directories. In the digital age, under-coverage is considered one of the most serious problems for digital survey research, as users on the web do not represent the population tout court, but just a part of it, sometimes with very specific characteristics (youth, high education, etc.). Boyd and Crawford (2012), for example, have noted that often researchers assume that internet users represent the population of a territory, underestimating that instead they are only a specific slice. Over-coverage refers to those units that are included in the population from which the sample is extracted even if they are not part of it. In the first two eras of the survey, such cases could occur using personal registers that continue to present immigrants or as alive, people already dead, or telephone directories that contain numbers that were no longer active or of transferred people. In the era of the digital survey, over-coverage problems can refer, for example, to that cluster of subjects, that despite being registered on sites, platforms and social networks, are not active subjects on the internet. As regards to non-responses, Gasperoni (1998), taking from Goyder (1997) distinguishes between the set of subjects on which information is desired (initial sample) and the set of cases on which it is actually possible to detect them (actual sample). The two sets may coincide but, usually, a more or less large proportion of units included in the initial sample escapes detection. Non-responses concern the impossibility, for some reason, of collecting complete information on all the units that are part of the sample. They are divided into two categories: full and partial refusals. Full refusals refer to subjects who do not grant any data and refuse a priori to become part of the research. The partial refusal of some questions concerns instead the subjects who participate in the survey but who refuse to answer specific questions. Non-responses are absolutely not to be confused with the under-coverage error. They concern those who were unable to enter the actual research sample because they were not present in the initial population and not, as in the case of non-responses, those who, after being contacted, refused to participate in the survey. A last case is made up of those with whom the researcher is unable to make contact. This latter can be a sign of over-coverage problems.

Regarding the selection errors, probability sampling has been the gold standard for social research, and non-probability sampling has been often heavily criticized; nevertheless in the recent times building probability samples is increasingly difficult, both theoretically and practically. In theory, in probability sampling all members of target population have a known nonzero probability of being sampled. It is difficult to satisfy the stringent conditions imposed by the probability models implicit in probabilistic samples because there are often problems of coverage and non-response. There is a big difference between probabilistic sampling in theory and probabilistic sampling in practice, which requires a series of statistical adjustments (e.g. weighting). The percentages of non-responses have increased enormously (in the case of commercial telephone surveys even up to 90%). The main problem is the statistical burden (Struijs, Braaksma, Daas, 2014), the exasperated request for information from the population for statistical surveys. In the statistically more advanced countries, the questionnaire and the sample survey have become widespread research methods used by private companies and public bodies, and this has generated annoyance in the population as well as distrust of the possibility of improper use of information (Amaturò, Aragona, 2012). Statistical burden has been a major problem for national and international statistical offices because it can affect the quality of data collected through questionnaires and interviews (Machin, 1998; Willeboordse, 1998).

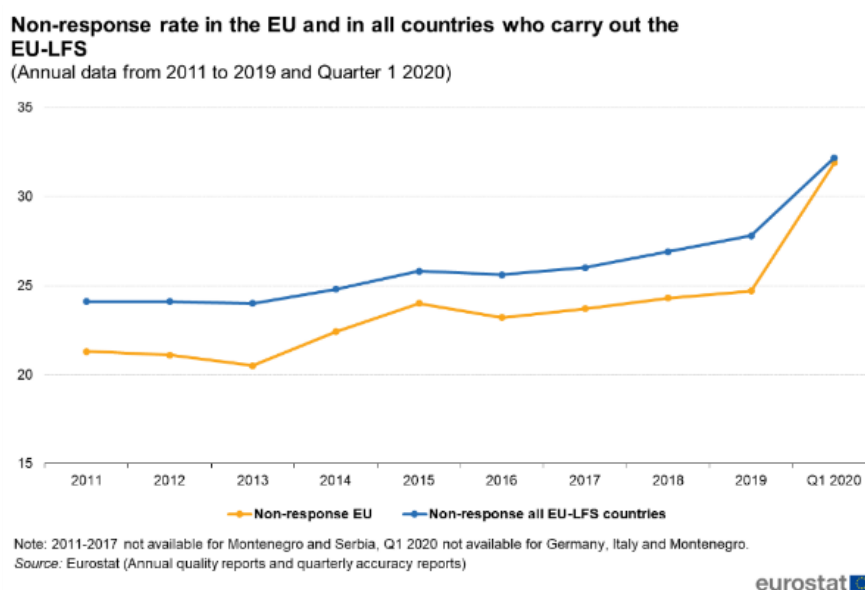
When the real probabilities of being included in the sample are not known, probabilistic and non-probabilistic samples become similar. Coverage errors and non-responses offer no guarantees to probability theory and inference depends on a variety of ex-post adjustments (e.g. weighting techniques).

In order to give some figures of how much non-response rates are increasing (Figure 1), in Eurostat surveys, which are high quality very expensive surveys, in ten years nonresponse rate increased 10%, even for the best survey, the Labour Force Survey. In commercial telephone surveys nonresponses are much higher, sometimes even as high as 90% (Kohut et al., 2012). All these non-responses make it difficult to draw precise inferences about the target population.

In the same time that there are growing difficulties for probability sampling methods, there have been great developments in non-probability sampling methods. For example, now digital platforms allow to access wide populations and to design quota sample with many stratification variables. Of course, researchers must take into account the coverage errors, but non-responses may be reduced at the minimum. If in the past the choice between probability and non-probability samples was straightforward, in the digital age researchers face a difficult choice between probability sampling methods in practice – which are increasingly expensive and far from the theoretical results that justify their use

– and non-probability sampling methods – which are cheaper faster, and of higher quality than in the past. Thus, when probability samples may have high nonresponse rates, the differences with non-probability samples must be carefully examined.

FIGURE 1. *Crescita delle mancate risposte nelle survey dell'EUROSTAT.*



In addition, we have to note that statistical methods for making inferences starting from non probabilistic samples have constantly progressed. Post-stratification methods, which are also widely used in the case of probabilistic samples to adjust for estimates with high coverage errors and non-responses, have improved sharply. The key to post-stratification is to properly define the groups that make up the population. If the population can be divided into homogeneous groups with respect to the probability of responding, post-stratification will produce non-biased estimates. This is an assumption of probability of homogeneous response in the group, which becomes more plausible as the number of groups increases. Creating many groups, however, can result in groups with few cases. Samples constructed using digital techniques can reach a very high number of cases, thus allowing greater fragmentation of the groups and therefore greater effectiveness of post-stratification. An interesting post-stratification method is multilevel regression with post-stratification (MR.P.), which allows to estimate the effects on a



population starting from data constructed on a sample that is not representative of that population (Gelman, Little, 1997). MR.P. combines two statistical techniques: multilevel regression, which considers the different predictors in a hierarchical way, and post-stratification, which allows adjusting the sample estimates when the differences between the population and the sample are known. There are numerous applications in the social sciences that through MR.P are able to generalize the estimates produced on non-probabilistic samples (Downes, 2018) and they mainly concern the use of data collected on online communities, and social network users.

Let us discuss now the second issue, measurement errors. The digital offers new ways to administer questionnaires. Web surveys have obvious advantages, such as, for example, the reduction of the time required for the survey, the reduction of costs, the almost immediate statistical processing of the data, and the possibility of customizing the survey questionnaire. Moreover, the main feature of surveys in the digital age is that the survey is fully managed by the computer rather than by the interviewers (as in the case of face-to-face and telephone interviews). This means eliminating social desirability and interviewer effects. Of course, there is the difficulty to keep the interviewee's attention high in a long questionnaire. Today, there are numerous online platforms that support the construction and dissemination of web surveys. But carrying out online surveys is not an easy task. In fact, the researcher is called to make choices on the many options available, which have significant effects on the overall results of the survey (estimates, response rates, measurement errors, etc.).

Interesting ways of asking are emerging, such as Wikisurvey (Salganik, Levy, 2015). Open questions and closed questions can give very different information. Open questions are rarely used because difficult to analyse, but they can be the most interesting ones as they open to the context of discovery. Wikisurveys allow us to enrich the possible answers to questions over time based on the answers of the participants to open questions. In New York, it was used to incorporate citizens' ideas into the city's sustainability plan. When asked about the better ways for creating a bigger and greener NY, 25 ideas were presented, but as citizens asked for their ideas to be included, after the approval of the administration they appeared among the possible answers. As Wikipedia, in practice, everyone can add a piece of the possible answer to a question.

Gamification is another interesting example. In this case the basic idea is that if you use games for asking questions, people are more keen to answer about serious themes. Tell me what your and your friends' tastes are on Facebook (Goel et al., 2010) is a famous example of gamification. This research was aiming to estimate how much people think to be similar to their friends and how much they actually are, but it is very difficult to interview both an individual

and his friends. An app was built on Facebook which, if a subject decided to participate, would ask him a question about the attitude of a friend of his. The respondent also answered questions about himself. The respondent was informed if the answer he had given was the same as his friend's. The questions were partly drawn from the General Social Survey (e.g. Does your friend pay higher taxes for the government to provide universal health care?), but were mixed with very light questions (e.g. your friend prefers wine or beer?, which superpower would you like to have?).

A different way to take advantage of digital methods is to link surveys to big data sources (Amaturo, Aragona, 2019). Big data and surveys can be adopted in succession or simultaneously, creating mixed designs. The mix can be for the methods of data collection or the inclusion of a preliminary pilot study, or even to carry out multilevel surveys that combine individual, contextual and relational units of analysis. Taking for example the forms of integration between quantitative and qualitative methods proposed by Creswell and Plano Clark (2017), adopting a pragmatic approach to the integration between survey research and big data. There are above all three ways of possible combinations of the two. What is called exploratory integration, that is, where big data research is aimed at fine-tuning the survey. Complementary integration – in which the two approaches are integrated in the joint data collection phase. Interpretative integration – which sees the use of big data to deepen and validate survey results. In the forms of exploratory integration, the big data approach precedes the survey approach; in the complementary integration the two are at the same level, while in the interpretative one the big data support the interpretation and validation of the results of a survey. One interesting example of mixing survey and big data is the case of the consumer price index. Istat (Italian national institute of statistics) is the first European statistical institute to introduce on a large scale the use of supermarket data scanners for calculating inflation. Until 2018, the survey was carried out through agents in about 80 municipalities, today through the data of over two thousand sales points, the most relevant part of the surveys of the so-called “grocery products”, like food and household products, takes place through bar codes. Only part of the surveys, that of small shops, will continue to be carried out with face to face interviews.

A final point that we would like to make is less optimistic than critical. The final quality of the responses to a digital survey strictly depends on the device used to respond. Web survey designers mostly collect data with rating scales that look like radio buttons, but they can also choose visual analog scales, often employed in the medical industry, or sliding scales, which are popular in market research. Many studies have shown that answers depend on the visual presentation of the questions. These visibility effects can be increased on cell

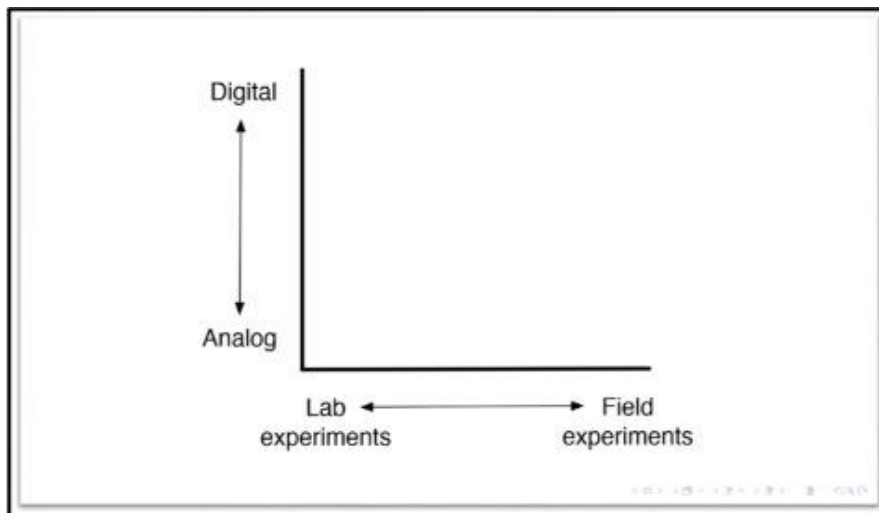
phones, which have smaller screens, especially when there are long response formats, with a large number of response modalities. A study conducted in the Netherlands (Toepel, Funke, 2018), which compared different ways of administering online questionnaires, asked respondents to complete a survey with a desktop personal computer, tablet or mobile phone. The results varied significantly by device type. Different devices may have consequences on selection and measurement bias. The position of an item on a screen varies by device, and depends on personal preferences. With the increase in the use of mobile internet, people expect surveys to be adapted to mobile devices. This changes the way online surveys should be designed. The study shows that the position of an element on a screen has a systematic, but not necessarily large, effect on responses. But effects on screen position can ruin comparisons if elements look different on screens. In order to reduce differences in the distribution of answers in a normal personal computer layout and in a mobile web layout, a responsive design must be used, i.e. a design in which the software detects the type of browser of the interviewee. However, respondents generally remain less satisfied with the mobile device than the regular web layout. In addition to positioning effects, response formats can also interact with the device used. Bars, such as scroll scales or visual scales, may become more popular response formats in the future because they require less space on a screen than buttons. With small screens on mobile phones, and because visibility determines the choice of response, evaluating the influence of response formats has become necessary in an age where people use different devices to answer questionnaires. Despite the efforts, there is still much to do to mitigate the impacts of digital settings on measurement and selection errors.

All these examples show how the digital may impact on surveys in many ways, and make us clearly understand that with digital social research, the beginning is not the end. As it has been noted, there have been many crises in the survey since it was born, and there have been just as many innovations in its history (Biolcati, Martire, 2018). Also for the third era of the survey, the digital one, we have some critical points and some innovations. If it is true that we need to know how digital survey is working now, it is more important think of how it will work in the future. What will happen when the data landscape will change, and researchers will become more aware of the potential? Researchers often focus on the first problem, but it is the second that is more important.

### 3. The digital experiment

Over time, experimental designs had lost more and more interest in the panorama of social research. With the digital, if surveys have entered a new era, also, and above all, experiments are experiencing a new renaissance in the panorama of social research methods. The digital does not change the nature of the experiment, but it makes logistic much simpler. Today, experiments may vary not only on the field-laboratory dimension but have another dimension along which they can differ: the analog-digital dimension (Figure 2).

FIGURE 2. Dimensions of experiments.



Source: (Salganik, 2018: 152).

Fully digital experiments are experiments that make use of digital infrastructures to recruit participants, administer treatments, randomize and track results. Fully analog experiments are experiments that do not use digital infrastructure for any of the four steps. Between the two extremes are the partially digital experiments, which use a combination of analog and digital systems. Building digital experiments can be very complex, but this is one line of development of digital social research that appears to be very promising.

There are many examples of the use of digital in the experiments. During the 2010 elections in the USA, *Facebook* and the University of San Diego carried out an experiment on 61 million users of the social network (Bond, Fariss, Jones, 2012). Users were divided into three different groups depending on which banner would be placed on top of their News Feed: 1) Control group; 2)

message information on the vote with the button “I voted” and a counter (Info); 3) message information on the vote with the button “I voted” and a counter (Info), and names and pictures of the friends who clicked “I voted”. The results showed that the messages directly influenced political self-expression, information seeking and real-world voting behavior of millions of people. Furthermore, the messages not only influenced the users who received them but also the users’ friends, and friends of friends. (Figure 3).

FIGURE 3. Messages published on Facebook during the election day.



Source: (Bond, Fariss, Jones , 2012), *Nature* 489: 295-298 doi:10.1038/nature11421.

This study is a clear example of how digital technologies can help in recruiting participants for experiments. Digital field experiments can have up to millions of participants. Increasing the number of participants is not only a quantitative change, but also a qualitative one, because it allows to deepen the

causal effects. In most of the analog experiments, the researchers focused on the average treatment effect, since the number of participants was limited. The possibility of observing how the effects are heterogeneous on the basis of the characteristics of the subjects participating in the experiment allows to formulate new theories and to reveal the causal mechanisms. Digital experiments help us to identify mechanisms and allow testing many interrelated treatments. If there are variables to keep under control, they allow a complete factorial design (with all possible combinations). In the past, a complete factorial design was difficult to control because it requires a large number of participants.

There are two possibilities for implementing digital experiment. In the previous example, researchers collaborated with a company (Facebook), but it can also be run without collaboration. Furthermore, it must be decided whether to experiment in existing digital environments, or build own system for experimenting. Using existing environments is the simplest way to carry out a digital experiment. Doleac and Stein (2013) in *The visible hand* studied the effects of race on local electronic market outcomes. They advertised thousands of iPods on electronic markets such as *Craigslist* and, by varying the characteristics of the vendor, they were able to study the effect of ethnicity on economic transactions. The ads varied in three characteristics: hand photographed (white, black, white with tattoo); misspellings (small letters); selling price. White sellers obtained higher final selling prices. In addition to the average effects, they estimated the heterogeneity of the effects. Discrimination was less in markets with higher supply: in this case the quality of the ad did not affect consumer's choice.

In addition to implanting our experiments in existing environments, we can also build new ones. The main advantage is control, it is possible to create the environment and the treatment. Furthermore, an ideal environment can be created to isolate the effects under investigation. The main disadvantages are the costs, which can be very high, at least the fixed ones. *Ipsos*, one of the world's leading companies in the study of consumer behavior tries to answer with its laboratory supermarket through a series of experiments that test products, to questions such as: what characteristics will the store of the future have? What packaging should a product have to be noticed and chosen on the shelf? What is the shopper's experience in a real store? Eye tracking is the technology used in this laboratory to suggest marketing decisions to companies. A fake supermarket, fake customers, a fake shopping list. Glasses to wear that record the movements of the gaze. In another room, experts analyze the behavior of those who lend themselves to the experiment. This is how the *Ipsos Company Market Lab* works. A supermarket is an environment full of stimuli, and body reacts differently to products, based on the position they occupy and their

packaging. *Ipsos*, which deals with marketing, has created “fake supermarkets” to analyze the behavior of those who wander around the shelves of a store and devise some strategies to increase stimuli and thus increase sales. Once they enter the market lab, participant must wear glasses equipped with an eye tracker, which will be able to capture the direction of their gaze. Participant must also be aware that movements will be captured by cameras and studied by some experts. After an initial calibration phase of the glasses, shopping begins: the fake customer is given a list of things to buy, and researchers observe how the search for these products is carried out. While the subject moves in the exact reproduction of a real supermarket, immersed in the noises (artificially reproduced) that one usually hears while shopping, all his movements are studied. The way he/she wanders among the shelves, the directions taken by his gaze, the final choice of goods. The amount of information that can be obtained is considerable, and it is no coincidence that *Ipsos*’ main customers are large-scale retail brands, who wish to test the effectiveness of the stimuli produced by different packages. The positioning of the products on the shelves, the ability to attract the customer’s attention, and the possibility of remaining in the memory of the buyer are analyzed. At the end of the experiments it emerges that there are brands that are ignored if placed next to others, and that in just three seconds our gaze is able to examine between 10 and 15 products. How much social science is there in this research? Well, certainly not a lot, but let’s think of the possibility that such technology opens up to social research. Think of the opportunity of testing the social influence of the peer group on purchases, or the influence of children on parental spending. The business objectives could immediately satisfy other more purely sociological objectives (Salganik, 2018).

Instead of doing experiments in the lab, digital experiments can also be created online, in environments built by researchers. A very particular example is LIONESS (Live Interactive ONline Experimental Server Software). This is an environment built *ad hoc* by researchers, but made available to other researchers who want to do interactive online experiments. Online experiments have typically used non-interactive tasks that participants complete on their own, the studies using designs with live interactions between participants have typically employed tailor-made software. As a result, the online use of interactive designs has thus been largely restricted to experimenters with advanced technical skills, or considerable financial resources. LIONESS is a free web-based platform that enables experimenters to develop, test, run, and share their interactive experiments online. The software is developed and maintained at the Centre for Decision Research and Experimental Economics (University of Nottingham, UK) and the Chair of Economic Theory (University of Passau, Germany) and can be accessed via <https://lioness-lab.org>.

LIONESS include a standardized set of methods to deal with the typical challenges arising when conducting interactive experiments online (Arechar Gächter, Molleman, 2018). These methods reflect current 'best practices', e.g., for preventing participants to enter a session more than once, facilitating on-the-fly formation of interaction groups, reducing waiting times for participants, driving down attrition by retaining attention of online participants and, importantly, adequate handling of cases in which participants drop out. LIONESS enables experimenters to share their experimental designs with co-workers and other colleagues, facilitating transparency and replicability of research. Participants access the experiment through a link, that is communicated by researchers. Experimenters can monitor the progress of a session through a control panel. Upon session completion, data can be exported as a spreadsheet ready for analysis. Platforms such as LIONESS for sure represent the possible future of digital experiments.

#### **4. Conclusions**

In 2007, an article titled "The Coming Crisis of Empirical Sociology" appeared in the journal *Sociology*. The authors, Mike Savage and Roger Burrows, warned their colleagues that the unprecedented availability of digital data on social behaviour and relationships, automatically recorded in real-time through the activities of users on platforms, would have rendered obsolete in a stroke the methodological apparatus of academic sociology, qualitative as well as quantitative. Seven years later, the same authors returned to the topic, this time from the pages of *Big Data & Society* (Savage, Burrows, 2014), quenching not a little the catastrophic tones of the previous article. Originally the revolution brought about by big data and digital methods was seen as a threat to traditional social research techniques. Years later, through this short roundup of examples we can instead firmly affirm that the digital has not at all led to the disappearance of research through interrogation and experimentation, but it has indeed opened a new season of social research in which the digital offers new possibilities for the use of this fundamental techniques of social research.

In conclusions, we can argue that critical optimism – a posture that can overcome both the worries about the end of traditional research methods, and the naive enthusiasms about the disruptive changes brought about by big data, computation and digital methods – is the right choice to unfold how research methods are evolving. The digital is an occasion to further develop traditional research methods: survey research is having a third era of development after the first era based on face to face interview, and the second era based on telephone; and experiments start to be employed in more and more research designs.



Critical optimism helps in asking the most important question: that is not what is the status of digital methods today, but what it is going to be in ten, twenty years. Critical optimism stops us thinking about the impact of the digital on social research methods, refocusing instead on the impact of social research methods on the future of the digital.

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