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Reducing Cognitive Biases Through Digitally Enabled Training. A Conceptual Framework

Samuel Collino Affiliationids : Aff1

Giancarlo Lauto

Email : giancarlo.lauto@uniud.it
Affiliationids : Aff1, Correspondingaffiliationid : Aff1

Aff1 Università degli Studi di Udine, 33100, Udine, Italy

Abstract

Since cognitive biases impair decision-making processes, organizations strive to reduce their effect. Training sustains such effort, especially when innovative learning approaches are adopted. The introduction of digital technologies, such as those related to Industry 4.0, challenges firms to upskill and reskill their employees. At the same time, these technologies offer a new set of tools for training. This paper proposes a conceptual model that disentangles the effect of the form of training and its reliance on digital technological tools, on the reduction of cognitive biases and performance in tasks related to digital transformations.

Keywords

Cognitive bias
Training
Technology

1. Introduction

Disruptive AQ1 technologies will bring significant shifts in the labor market requiring workers and management to develop a completely new set of skills [43]. Technologies enabling automation, artificial intelligence, and machine learning, often labeled as Industry 4.0 [20], are fostering an evolution of the social and industrial environment with huge impacts on production systems, creating the possibility to disrupt an increasing number of tasks. The digitalization of product and processes appears even more urgent now, in light of the unpredictable consequences of the COVID-19 outbreak on the organization of work and of global value chains [44].

This rapid technological shift is bringing a great productivity increase potential, but also opening a transition phase. It seems that competence creation processes can take place at a slower speed when compared to technological change. This would result in gaps between skills required by firms and skills possessed by the workforce. Therefore, it emerges a need for reskilling, that is possible through innovative forms of training [4, 10, 13].

Digital technology-enabled forms of training promise to endow employees with the skills needed to operate effectively in this new industrial setting as well as to enhance their existing skills. In this paper, we focus on the latter, by outlining a conceptual model that disentangles the effect of digital technology-enabled training on the impact of cognitive biases on decisions within the setting of operations management.

The study of cognitive biases is gaining relevance for operations management as this filed is embracing a more human-centered view in its investigation, which entails the full recognition of the bounded rationality of actors and the emphasis on behavioral dimension of the process. This field appears therefore open to fruitful contamination with a well-established stream of studies in Psychology and Organization.

In this piece of research, we study the cognitive biases not only by the adoption of a new heuristic more unlikely to lead to a severe systematic error, but with the adoption of new technologies. Training and specifically innovative forms of training have been shown to be effective in reducing and preventing cognitive biases. But may technology play a role in this relation, by means of reducing cognitive biases when performing a new task?

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2. Including the Human Side in Operations Management

2.1. Toward a Behavioral View of Operations Management

The field of operations management is changing toward the inclusion of behavioral factors into its scope of analysis. From being a niche subfield, behavioral operations research has more than doubled the number of scientific publication between 2006–2012 and 2013–2017 [15], evidencing a growing interest on the topic, a vibrant methodological pluralism—leveraging on an experimental approach—and expanding from the original topics of supply chain management, product development, quality and production, to new areas of investigation [12] such as retail, healthcare operations, and social and sustainability decisions [15]. What links together these studies, and differentiates them from the earlier streams of operations management research, is the deviation from a hyper-rational conceptualization of decision making in the context of operations management that has long characterized the field [12].

Traditionally, operations management studies have assumed that decisionmakers, problemsolvers, and workers are rational or that can be induced to behave rationally [18]. As [17] put forward, rational or intentionally rational decision making rests on tools such as logical reasoning or statistics, and operations management research as much emphasized mathematical modeling as statistical testing as a way to advance our knowledge about production systems and to offer managers sound operational tools. However, it has also been suggested that in operations management "…techniques and theories ignore important characteristics of real systems, and therefore are perceived to be difficult to apply in practice. A common factor in this breakdown is people" ([5]: 737). To address this shortcoming, the study of operations management has added to its analytical models factors such as people's actions, emotions, reactions, and intentions [15]. Behavioral operations management is a multidisciplinary branch of operations management that explicitly considers the effects of human behavior in process performance, influenced by cognitive biases, social preferences, and cultural norms [26].

The idea of a non-hyper-rational individual is not new in Organization Studies, at least since Herbert [35] development of the notion of bounded rationality. However, the field of operations management seems to be lagging behind in the adoption of such perspective, as, still recently, [12] suggested that any behavior that deviates from the hyper-rational is a candidate for research in that field of studies.

Simon's well-established notion of economic agents is incapable of acquiring, processing, and deploying information with complete mindfulness that has revolutionized management scholarship as it offered a more compelling alternative to the dominant conceptualization of the "homo oeconomicus" that still characterizes much of operations management research. Furthermore, Simon's contribution has emphasized that agents are not capable of always taking rational decisions due to unavailability of complete information (informational limit), and inability to correctly interpreting and processing (computational limit) the limited information available, due to boundaries in time and cognitive limitations of their mind.

2.2. The Role of Cognitive Bias in Operations Management

Deviating from the tenets of perfect rationality, it is essential to acknowledge that decisionmakers adopt other tools, in addition to logic and statistics, such as heuristics. Building on a wealth of studies in behavioral sciences ([17]: 454) offers a definition of heuristic as "*a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods.*" With specific regard to psychology, [24] defined psychological heuristics as formal models for making decisions that:

(i) rely heavily on core psychological capacities (e.g., recognizing patterns or recalling information from memory);

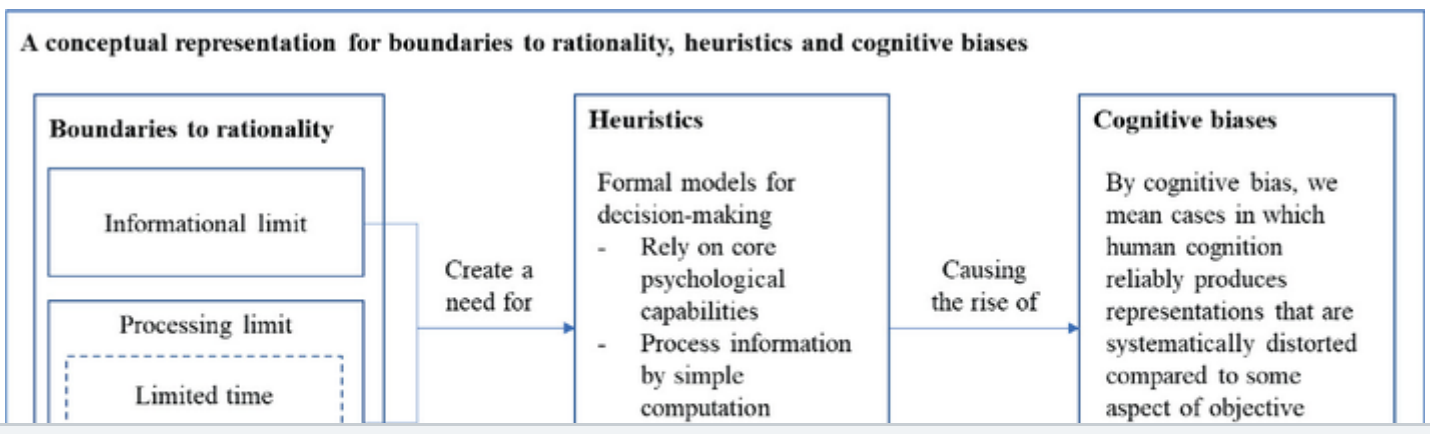
(ii) do not necessarily use all available information and process the information they use by simple computations (e.g., ordinal comparisons or unweighted sums);

(iii) are easy to understand, apply, and explain.

Figure 1 offers a comprehensive view of the conceptual linkages between the notions of bounded rationality, heuristics, and cognitive biases.

Fig. 1

A simplified conceptual framework on boundaries to rationality, heuristics, and cognitive biases



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Simplified heuristics, such as representativeness, availability and adjusting and anchoring have been shown to potentially lead to a series of cognitive biases, which in evolutionary psychology are meant as "*cases in which human cognition reliably produces representations that are systematically distorted compared to some aspect of objective reality*" and systematically hinder someone's ability to rationally perform a task or set of tasks ([19]: 968).

A famous example of cognitive bias is this experiment performed by [38] related to decision-making task, that highlights the relevance of information visualization, and specifically of framing in describing a problem outcome in the decisions patterns of two identical problems. Participants were posed the following problem:

Imagine the U.S. is preparing for the outbreak of an unusual Asia disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs are as follows:

If Program A is adopted, 200 people will be saved.

If program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved.

Program A was preferred by 72% of participants.

The authors then presented the same problem to a different sample with the following outcomes to choose:

If Program C is adopted 400 people will die.

If program D is adopted there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die.

Program D was chosen by 78% of participants.

This simple, yet powerful experiment, shows how choices involving gains are risk averse and choices involving losses are risk taking. The two problems are though identical from a probabilistic point of view, yet they achieve opposite results, where the only difference comes from framing the outcomes in a positive or a negative way.

The seminal contribution by [37] identified three bias categories originating from heuristic processes, namely representativeness, availability, and anchoring, which affect decision making. Then, the researchers grouped them based on the hypothesized heuristic strategy that the individual follows in taking the decision.

The representativeness heuristic implies that during a judgment process, probabilities are evaluated by the degree to which A is representative of B, for example by the degree of similarity between them. However, several factors needed to assess likelihood do not play a role in judgments of similarity. Availability refers to the tendency to assess the frequency of an occurrence based on the easiness of recalling an event or topic in mind. Adjustment and anchoring bias the person making an estimation toward the initial value that has been anchored, for instance building on previous data or a partial estimation, where the following adjustment is not sufficient to lead the judging person to the real value.

Since the 1970s, many cognitive biases have been found [23], and efforts have been made in reviewing and categorizing them (e.g., Baron, 2000, [2]). Interestingly, [14] recently built on in a comprehensive task-based taxonomy that appears particularly useful to identify the biases that might occur when performing different tasks. In this analysis of cognitive biases in information visualization, the authors categorized a broad range of 154 biases into bias "flavors" and "task categories." The "flavors" build on the heuristic concept and try to capture the phenomenon behind the bias, as much previous studies do. These flavors are [14]:

(1) Association, where cognition is biased by associative connections between information items.

(2) Baseline, where cognition is biased by a comparison with (what is perceived as) a baseline.

(3) Inertia, where cognition is biased by the prospect of changing the current state.

(4) Outcome, where cognition is biased by how well something fits an expected or desired outcome.

(5) Self-perspective, where cognition is biased by a self-oriented view point.

The biggest contribution in this piece of research was the identification of six defined "task categories" in which systematic biases found in the previous literature can be divided. These tasks are:

(1) Estimation, where individuals are asked to forecast the quantity or the probability of an occurrence. Biases in this task category include, for example, anchoring, availability, and spotlight effect.

(2) Decision, or choice tasks, refer to situations in which people make choices on a set of alternatives and tend to be systematically biased toward one of them. Examples of biases in this category are framing, automation bias, and status-quo bias.

(3) Hypothesis assessment tasks refer to cases in which people needs to confirm or reject a hypothesis conducting an investigation. This category includes a smaller number of cognitive biases, but nevertheless very relevant to the field, such as the confirmation bias, in which people tend to confirm previous hypothesis rather than disprove it.

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(4) Causal attribution tasks are also prone to cognitive biases. In this situation, individuals are asked to find root-causes and effects of phenomena, where the bias induced derives from their view of themselves, their empathy toward the part involved in the situation, or their belonging to one group over another. Some biases categorized in this task include the group attribution bias, in which group traits are attributed to an individual belonging to this group, or egocentric biases, in which the own contribution is perceived as disproportionately higher in comparison to others.

(5) Recall tasks are those in which individuals seek to remember past experiences or knowledge after some time has passed since the event, and misinterpretation or other factors have had the time to occur. Some of the biases occurring include, as an example, digital amnesia, that makes it more difficult to retrieve data easily available thanks to digital solutions. On the opposite, the bizarreness effect makes it easier to remember facts and situations when they are out of the perceived normality. Also, the misinformation effect is an example of bias in this category. In this case, memory is enriched with new pieces of information that were not included in the original experience or knowledge.

(6) The last category of systematic biases includes the biases occurring when asking individuals to report others' opinions, mostly on situational sensitive topics. It has been observed that often participants to studies on such biases misreported others' opinions according to specific biases, such as stereotyping, which makes an individual attribute to someone some traits associated to a group he belongs to, or the focusing effect, for which reported beliefs are based on the main and most spoken portion of a message.

Cognitive biases affect a number of different areas related to operations management such as process assessment and risk assessment [28]. Various field and laboratory experiments, e.g. [3, 7], confirm the relevance and vast diffusion of this potentially dangerous downside.

3. What Training for Developing Operation Management Skills

Training has been demonstrated to be an effective mean to reduce the occurrence and effects of cognitive biases in different tasks and settings [27, 34]. Many debiasing strategies have been proposed through training, such as rising awareness on biases, their directionality, and the importance of feedback and coaching. However, the efficacy of training in addressing these biases is associated with the design of the interventions.

Training can be conceived as a learning and development process aimed at increasing organizational performance by endowing people with the knowledge, skills, and competencies need to carry out their work effectively and successfully (Armstrong & Taylor, 2020). The main domains affecting training efficiency concern [25]:

- Trainee characteristics
- Training design
- Training transfer climate
- Work environment.

For what concerns the training design, it is useful to distinguish traditional, scenario-based cases, and problem-based experiential learning. The two latter forms of training are particularly effective in achieving the purpose of knowledge transfer in a perspective of reskilling and upskilling [34].

Traditional forms of training take the form of frontal lectures in classrooms and apprenticeship for repetitive tasks with the demonstration of an activity to trainees, until they become able to perform it [21]. One of the assumptions of traditional teaching methods is the predictability of tasks in a stable environment, while in an evolving situation with growing uncertainties it is necessary to create adaptive expertise.

Such adaptive experiences may be offered by exposing trainees to cases portraying different scenarios in a real setting, to "learn during their experiences while addressing desired goals" [32, 33]. The development of goal-based scenarios seems to have risen from a critic of traditional training methods concerning the drift toward an excessive emphasis on verifiability and standardization of knowledge, where facts are considered as basic notions with no real-life meaning or implication. To create a scenario-based case study, namely a "learn by doing course," it is necessary to combine simulation and case-based reasoning. The learner has a role to play, which can vary according to observed, real interests of the student, avoiding artificial world problems [33].

The development of problem-based learning training modules entails the following activities [8]:

- Description of the problem provided to the student. The problem may be described either in neutral, clear, non-contradictory, realistic terms and refers to a fairly common setting [8], or in an ill-defined fashion with the aim of involving trainees into the development of a complex solution and stimulating the analytical skills of participants [1]. Realism, complexity, and contradiction are on the other side probably characteristics of the working environment in which the trainees will have to apply the skills acquired during the learning.
- Definition of the scope for the problem solving activity.

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- Time management. The time allocated to training activities is generally insufficient to address all the issues raised by the problem. A need for prioritizing the activities and allocating the cognitive effort emerges. It should be noted that participation is positively related to the sense of urgency for the problem.
- Design of cognitive conflict and social negotiation opportunities, that should be seen as a stimulus for learning through the evaluation of viability of individual understanding. To this purpose, it is important to encourage to test ideas rather to accept alternative views.

Problem-based learning is probably the most widely adopted experiential learning method within executive development programs [45]. Indeed, live projects, a concept very similar to experiential learning, have the highest positive result in terms of successful skill transfer, and, in general, teaching methods that trigger the student to acquire additional knowledge on his own may result in a more positive outcome [29]. Although it is a very effective and motivating technique, it is very time-consuming, and therefore not particularly efficient [8].

4. How Industry 4.0 Technologies May Attenuate Cognitive Biases

Some of the technologies that are part of the broad Industry 4.0 landscape promise to help to remove or attenuate both the causes of cognitive biases: the unavailability of information and the human capacity to process information.

In 2013, a group of practitioners and academics at the yearly Hannover Messe enshrined in a Manifesto a set of recommendations for implementing what was called "Industrie 4.0" [20]. The trend of automation and smart system development in both physical and intellectual contexts emerged decisively, interpreting and linking different new technologies that grew in the beginning of the new millennium, ultimately aiming at keeping competitiveness high, also through an optimized decision making.

For instance, the Internet of things allows for the collection of data through sensors and stacks that contribute to the creation of big data and data lakes constituting an organization's backbone for a data-based decision making. It is a new paradigm of interconnection of final goods exchanging information to provide data, optimization, and self-control in the most advanced examples, which are transforming the business world [30]. This concept shares many of the characteristics of "smart factories," where Xia [42] points out ubiquity, interconnection, glocalization, and traceability as core enablers and constituents of this new paradigm made possible by the low costs of these new technologies and their miniaturization. A further step has been the interconnection of production facilities to this network, captured as the paradigm of the industrial Internet of things [16]. This further step creates significant implications not only for strategic and marketing-related activities, but also for areas of the field of operations management, for example in production, capacity management, and supply chain decisions.

Building on the same technological ground, also lean-empowered product lifecycle management [22] can now provide an increased and improved amount of information feeding the product development process, leveraging on big data [41] and cloud to facilitate the exchange and usability of the collected data and information. Many examples of successful industrial implementation of these concepts now exist from aerospace, automotive [9, 39], and prove the advantage provided by an enriched base for data-driven decision making.

While some technologies help to solve the information availability issue, others address problem of information processing. For instance, one of the key principles identified in Industry 4.0 is the adoption of knowledge tasks automation systems, such as Robotic Process Automation systems [40] and smart assistance systems, which have the scope of releasing workers from having to perform routine tasks, enabling them to focus on creative, value-added activities [20]. In this, Industry 4.0 promises to grant more time for individuals inside organizations to take decisions of higher quality, reducing the information processing boundary to rationality.

At the same time, other technologies allow for a better use of this information during the allocated time, enhancing an individual's ability to select, acquire, and process relevant information. This is the case of wearable technologies, able to convey information in more ways than traditional, static visualization, and of virtual reality (VR) when compared to traditional monitor visualization, thanks to its vividness and interactivity [36] and by immersing the individual in a new, safe to experience of reality, recognizing the need for a better intermediation tool to enhance the cognitive abilities of humans [11].

Augmented and mixed reality go further on this, by bridging the physical and cyberworld [31], enhancing human comprehension and information processing abilities by adding additional layers of information on the reality they see. The application fields are broad, as are the potential gains, that include an improvement of visualization, for example allowing for the inspection of internal components otherwise difficult to see, adding the possibility to test in a safe environment even complex tasks for operators, giving instructions, training, and coaching [31]. Further applications included the use of augmented reality for prototyping and product testing [6], demonstrating their usefulness as technological tools able to enhance humans' information processing ability.

5. How Training and Advance Technologies Help to Offset Cognitive Biases. A Conceptual Model

The inclusion of human factors into operations management has been a necessary step toward a better understanding of the real-world issues by overcoming the well-established hyper-rational conceptualizations. Embracing the perspective of bounded rationality implies

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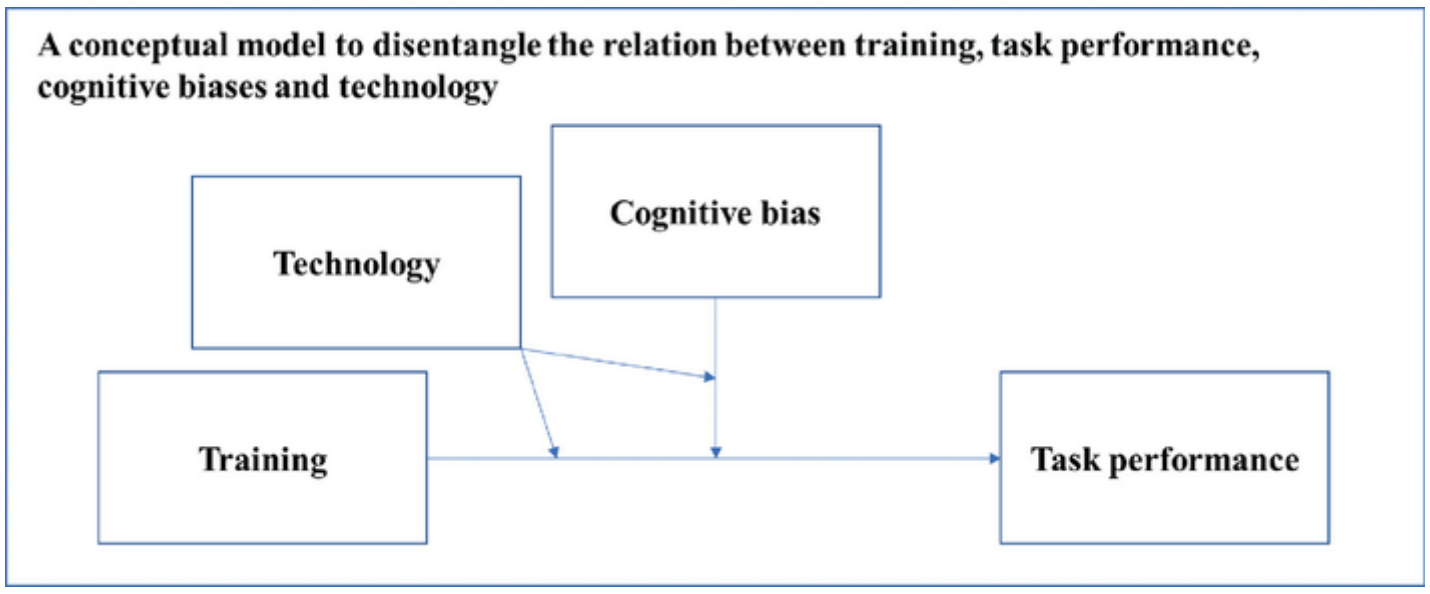
the necessity of acknowledging the effect of cognitive biases on task results. Various studies have then analyzed how tasks in different fields of operations management can be prone to such biases, but training has proved to be an effective way to impair their effect.

The introduction of new technologies—such as those brought by the digitalization of production processes according to the Industry 4.0 paradigm—demand a reskilling and upskilling of employees who are asked to perform new, richer, and more complex tasks. Training is therefore an essential activity to perform in this new industrial setting.

On the ground of such considerations, we propose the model portrayed in Fig. 2 to study the relation among training, cognitive biases, adoption of new technologies and task performance.

Fig. 2

A conceptual model for the study of the relation between training, cognitive biases, technologies, and task performance



Our model posits a direct relationship between training and the performance of operators in carrying out both existing tasks and new tasks introduced by the adoption of novel technologies. In the latter case, the training effort is more substantial, as employees need to learn completely new skills, competences, behavior, and attitudes, since their job may be redefined. However, training is essential even in the case of established tasks, as the adoption of new technologies may alter the context in which such task is performed. An example may be the activity of safety check in a production plant that adopted Industry 4.0 technologies. In such an environment, old and new hazards coexist and the tasks of employees who perform safety check change and potentially become more complex.

We expect that innovative forms of training—such as problem-based scenarios, simulations, and role-play—are powerful in improving the operators' performance in carrying out a task, by virtue of their ability of delivering knowledge through a more engaging approach.

However, as previously discussed, operators are prone to cognitive biases while making the decisions required by the task. Through training, operators may learn to be aware and recognize such biases and therefore their effect may be attenuated. We expect that different models of training have a different level of efficacy in attenuating the effect of the biases.

Furthermore, we acknowledge the role of technology as a support for training provision as well as the object of the training. On one hand, the use of technology could enhance the training, offering a richer learning experience. For instance, the use of VR tools that simulate a shop-floor where hazards such as wet floor or incorrect storage are present may offer trainees a more realistic experience, improve the delivery of content, and make trainees more aware of the biases that they may incur when they are evaluating the hazards of a real shop-floor. In this sense, digital technologies contribute to debias complex tasks and eventually improve task performance. On the other hand, the use of digital technologies for training may induce other series of biases, associated with the very use of such tools. Trainees may show a different performance in the training and in their operative activities, due to the fact that the training has relied on a specific medium for the delivery of the content. Indeed, the performance in the training may be due to the novelty for the subject of new technological tools, while it might fade away if the technology is repeatedly used.

Such conceptual model can be empirically tested in an experimental setting. In such experiments, trainees may undergo different forms of training, such as frontal lectures, cased-based simulations, and digital supported training. Training may address either a task that has been improved thanks to the application of digital technologies or a completely new one. Trainees can be induced different kinds of cognitive biases (e.g., anchoring or overconfidence) through scenario-based manipulations. The joint effect of training method and cognitive biases should be appreciated in terms of learning as well as in terms of change of behavior in the long term.

Disentangling the relationship between new digital technologies, training and cognitive biases on task performance would contribute to the development of the field of behavioral operations, as outlined by [18]. This effort would also provide evidence of the benefits of the adoption of new technology-based tools when performing tasks that might be prone to cognitive biases, even when debiasing training has been put in place.

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