When Ignorance isn't Bliss: Managers' Illusion of Explanatory Depth for Emerging Digital Technologies and the Promise of Visualization

Abstract

This article examines the effect of visualizing one's own understanding of digital technologies on the self-calibration of knowledge in the context of a specific knowledge bias, the "illusion of explanatory depth". In two experiments, we investigate the size and impact of this illusion on experienced managers and their understanding of contemporary and strategy-relevant emerging digital technologies and examine the potential debiasing effect of self-sketched visualizations on the self-calibration of managerial knowledge. The findings show that experienced managers suffer from a significant illusion concerning their understanding of strategy-relevant emerging digital technologies and that visualizing one's current level of understanding supports the accurate calibration of one's knowledge. Thus, this research stimulates the extension of existing theory on overconfidence and especially overestimation in strategic management. The findings point to the promise that sketched visualizing is a helpful modality for the detection and subsequent re-calibration of biased knowledge.

Keywords

Debiasing, illusion of explanatory depth, overestimation, strategic decision making, visualization,

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Introduction

Following the demand "to gain deeper insights into the *cognitive* and emotional significance of strategy practitioners' behaviors" (Hodgkinson and Clarke, 2007, p. 244), our studies look at one crucial factor of managerial strategizing: the *knowledge about one's own knowledge*, its impact on strategic decisions, and how managers can make these knowledge gaps explicit to improve strategic decision making. To do so, we apply a seminal concept from cognitive psychology to the strategy realm, namely the *illusion of explanatory depth* (IOED) (Rozenblit and Keil, 2002). This article combines three angles: A deeper understanding of the size of this cognitive limitation of strategy practitioners when it comes to emerging digital technologies, the impact of these limitations on strategic decisions, and an analysis how self-sketched visualizations may help to calibrate one's own knowledge and thus reduce one's overestimation of knowledge. As a consequence, the article provides scholars and managers with insights of how an IOED about emerging digital technologies may flaw the outcome of strategizing and how and why self-sketched visualizations may help to mitigate this effect. In the first part of this article, we focus on the importance of understanding emerging digital technologies from a strategic decision-making perspective, the challenge of an incorrect calibration of this knowledge which leads to overestimation, and the promise of visualizations in strategic decision-making to correct this overestimation or knowledge illusion. In a second part, we develop two hypotheses concerning the influence of the IOED in strategic decision making and the potential calibration effect of self-sketched visualizations. This leads to the design of two experiments testing both hypotheses, the results, and the final discussion and conclusion.

Understanding Emerging Digital Technologies

The understanding of emerging digital technologies (such as blockchain, the internet of things, or artificial intelligence) is a prerequisite for successful digital business transformation (Berghaus and Back, 2016; Ismail, Khater, and Zaki, 2017; Rachinger, Müller, Rauter, Vorraber, and Schirgi, 2018; Westerman, Calméjane, Bonnet, Ferraris, and McAfee, 2011) or as Yoo *et al.* write: "digital technology is an integral

part of strategy formulations" (Yoo, Henfridsson, and Lyytinen, 2010, p. 730). The lack of understanding for novel, emerging technologies feeds uncertainties in regard of their economic potential and value creation (Kapoor and Klueter 2021) as such an understanding and a potential adoption requires significant knowledge and experience (Shih 2020). The digital maturity of a company (Gill and VanBoskirk, 2016; Remane, Hanelt, Wiesboeck, and Kolbe, 2017; Westerman, Tannou, Bonnet, Ferraris, and McAfee, 2012) and the knowledge of managers about strategy-relevant emerging digital technologies (Brockmann and Anthony, 2002; Eisenhardt, 1989; Smith, Collins, and Clark, 2005) is hence critical for strategic decisions. The underlying challenges of uncertainty in digital maturity and knowledge about emerging digital technologies are "managerial cognitive processes that relate to attention, perception, reasoning, and problem solving" (Kapoor and Klueter 2021, p. 69). Thus, processes like the accurate self-assessment of this knowledge (Furnham and Boo, 2011), to understand the strengths and weaknesses of emerging digital technologies like artificial intelligence (Shrestha et al. 2019) and their rapid adoption (von Krogh 2018) have become crucial for the strategic decision-making process (Fitzgerald, Kruschwitz, Bonnet, and Welch, 2013; Kane, Palmer, Phillips, Kiron, and Buckley, 2015; Westerman, Calméjane, Bonnet, Ferraris, and McAfee, 2011).

A flawed understanding of emerging digital technologies, an over- or underconfidence in one's own knowledge, may be hazardous as it, among other things, may seduce managers to overly rely on their own (flawed) expertise instead of seeking advice from experts or other internal or external collaborators (Alba and Hutchinson 2000, Radecki and Jaccard 1995, Singh et al. 2015, Walters et al. 2017) – and as a consequence, leads to poor strategic decision making when it comes to the assessment of emerging digital technologies and their potential value creation (Kapoor and Klueter 2021).

The Effect of Exceeding Confidence in One's Own Knowledge

Overconfidence in strategic decision making has been recognized as a powerful cognitive limitation or bias with an ambiguous influence on decisions (Barber and Odean 2001, Busenitz and Barney 1997, Camerer and Lovallo 1999, Malmendier and Tate 2005). It is "one of the most consistent, powerful, and

widespread" (Johnson and Fowler, 2011, p. 317) cognitive biases: "No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence" (Plous, 1993, p. 217).

The impact of overconfidence on managerial decision has been shown in various contexts: Overconfidence in one's own abilities leads to business entry mistakes (Camerer and Lovallo 1999) and influences risk taking (Schumacher et al. 2020). It leads "to conclude that a situation is less risky" (Busenitz and Barney, 1997, p. 25), and the overestimation of investment returns results in an overpay for target companies (Lee et al. 2017, Malmendier and Tate 2005), and excessive trading (Barber and Odean 2001). Overconfidence in strategic decisions is ambiguous as it "may be particularly beneficial in implementing a specific decision and persuading others to be enthusiastic about it as well" (Busenitz & Barney, 1997, p. 10), but it also threatens the quality of decision making as it crowds out decision aids, ignores the base rate, fosters groupthink and induces a failure to consider alternative perspectives (Arkes, 2001, p. 496–497). The phenomenon of overconfidence increases in "unfamiliar or poorly understood strategic contexts" (Johnson and Fowler, 2011, p. 319), and "when organizations undertake novel tasks and when top managers, who do not face strong social feedback from peers, are the ones taking action" (Dunning, Heath, and Suls, 2004, p. 93). Thus, overconfidence increases in "precisely the most dangerous of situations" (Johnson and Fowler, 2011, p. 320) – and, precisely, the situation strategists find themselves when being confronted with novel, emerging digital technologies.

Overconfidence is known as a "positive illusion" (Haselton, Nettle, and Andrews, 2015; Taylor and Brown, 1988) consisting of different phenomena: a) an unrealistic positive view of the self (Taylor and Brown, 1988, p. 195) or exaggerated personal qualities and *capabilities* (Johnson and Fowler, 2011, p. 317), b) the illusion of control (Johnson and Fowler, 2011, p. 317; Taylor and Brown, 1988, p. 196), and c) unrealistic optimism (Taylor and Brown, 1988, p. 196) or negligence to risk (Johnson and Fowler, 2011, p. 317). Moore and Healy (2008, p. 502) summarize these phenomena as "overestimation" and add *overplacement* (people believe to be better than others) and *overprecision* (an excessive certainty about the accuracy of one's believes) to the concept of general overconfidence.

In this article we focus on one specific aspect of overconfidence: the *overestimation* of managers' own explanatory knowledge in the context of strategic decision making, or in other words *"the mismatch between what they think they already know and what they really know*" (Rozenblit and Keil, 2002, p. 524), the illusion of explanatory depth (IOED). In contrast to the overestimation of factual, procedural, or narrative knowledge, the specific IOED shows an overestimation of one's understanding of complex causal relations, the *explanatory knowledge* of how things and particularly technologies work.

We have chosen to explore this specific perspective of overconfidence and overestimation as the lack of understanding emerging digital technologies (NOT being able to explain these technologies to oneself and to others involved in a decision-making process and NOT being aware of this lack) feeds uncertainties (Kapoor and Klueter 2021) and a (re-)calibration may support an accurate self-assessment of this knowledge (Furnham and Boo 2011). This also follows the call for more research on the effects of calibration of different kinds of knowledge in strategy research (Pillai 2010).

Calibration of Knowledge and the Promise of Visualizations

A miscalibration is a deviation from the accuracy of the decision (Tang et al. 2014). Thus, calibration helps to close the gap between the expressed confidence (subjective confidence) and the accuracy of a decision (objective quality) (Koriat 2012, Sniezek and Henry 1989, Tang et al. 2014). Calibration raises the degree of certainty (Alba and Hutchinson 2000), reduces the tendency to take inappropriate actions (Maule and Hodgkinson 2003) based on inaccurate managerial perceptions (Pillai 2010), and improves information search in consumer decisions (Pillai and Hofacker 2020).

"Perfect calibration exists when one's belief in the veracity of the knowledge (confidence) matches the correctness of that knowledge (accuracy)" (Pillai 2010, p. 301).

The calibration of knowledge can be achieved by training (Gutierrez de Blume 2017, Moore et al. 2017) or by feedback on the accuracy of one's judgement or decision (Tang et al. 2014). The findings on feedback as calibration method show an hard-easy effect: feedback for difficult tasks provide a better calibration than for easy tasks (Keren 1988, Petrusic and Baranski 1997). This hard-easy effect is a result of the fluency effect, the subjective impression of how hard or easy a decision is (Zwaan and Hautz 2019).

Another way of calibration is the deliberate reflection, "to go back to the case" (Costa Filho et al. 2019, p. 231), which facilitates a disfluency effect by lowering the confidence (Sniezek and Henry 1989) and retrieving the unknowns (Walters et al. 2017) and thus supports the calibration of knowledge. In contrast, the ease that is facilitated by fluency leads to greater use of heuristic reasoning, and sometimes more errors in judgment" (Hernandez and Preston, 2013, p. 178), thus "processing fluency may be one important factor that determines when people will overcome their intuitive responses to engage more systematic reasoning" (Alter et al., 2007, p. 575).

Following the dual coding theory by Paivio (1986), a deliberate reflection bases on two forms of mental representations: verbal and visual (imagery). Affordances of visualizations such as tangibility (making knowledge visible and concrete) and associability (relating different issues or perspectives to each other) (Paroutis et al. 2015), or the provisionality or small degree of perceived finishedness (Bresciani and Eppler 2018, Hundhausen 2005) give images the potential to improve "communication, comprehension, recall and motivation compared to text or discourse alone" (Paroutis and Knight, 2019, p. 207). Visualizations such as diagrams, maps, sketches, or metaphors (Eppler and Burkhard, 2007) can improve reasoning (Bauer & Johnson-Laird, 1993) and comprehension (Tversky and Kessell, 2014) by visualizing thought (Tversky, 2011) and help to mitigate the attraction or decoy effect in decisions (Dimara et al. 2019).

Over the last years, the use of visualizations in strategizing episodes and strategic decision making has received more and more attention. Graphic representations support the strategic planning process (Eppler and Platts 2009), help to map strategic consensus (Tarakci et al. 2014), and support transparency and inclusion in open strategy contexts (Paroutis and Knight 2019). The use of visualizations enhances strategy tools in their interactive role to facilitate creativity, meaning, discourse and knowledge creation and sharing in strategizing (Jarzabkowski and Kaplan 2015, Knight et al. 2018, Paroutis et al. 2015, Pfister and Eppler 2012). It also supports the subsequent communication and hence implementation of strategies (Kernbach et al. 2015). Hodgkinson et al (1999, 2004) showed that drawing cause maps before a decision attenuates a framing bias.

Compared to other ways of visualizing mental representations like diagrams, maps, or images, sketching has several strengths (Eppler and Burkhard 2007). Sketches are fast and no artistic skills are necessary which provides a low entry barrier for its use in strategizing (Walny et al. 2015). Sketches are imprecise, unfinished with a careful fuzziness and thus "non-threating" as they make abstract principles and knowledge easier handleable and bring unconscious nuances to consciousness (Platts 2001). Their vagueness and amorphousness allows to display and accept uncertainties (Swedberg 2016). External visual representations like sketches help to coordinate external and internal perspectives and allow people to compute more deeply, broadly, and more precisely, to "communicate with themselves" (Kirsh 2010, p. 444) through the incremental and "step-by-step" process of sketching knowledge.

Given these benefits of visualization and especially self-drawn sketches, we ask the following explorative question: Can self-sketched visualizations help to (re-)calibrate one's knowledge of emerging digital technologies to uncover and even correct the illusion of explanatory depth as miscalibration of knowledge?

Hypotheses

The Impact of an IOED and its Calibration in Strategic Decision Making

The specific phenomenon of an illusion of explanatory depth emerges because of "people's limited knowledge and their misleading intuitive epistemology" (Rozenblit and Keil, 2002, p. 522) in the self-assessment of the understanding of complex causal patterns. It leads to an inaccurate self-assessment of one's own knowledge (Fisher and Keil, 2016). Rozenblit and Keil (2002) define four features of knowledge prone to an IOED: the confusion of the internal representation and the environmental support, the confusion between the different levels of analysis, the complexity of hierarchies of explanation, and the rarity of reproduction of an explanation. The understanding of emerging digital technologies and their complex causal patterns fits this definition of "explanatory, theory-like knowledge that may converge to convince people they have vivid, blueprint-like senses of how things work, even when their actual knowledge is skeletal and incomplete" (Rozenblit and Keil, 2002, p. 522). Emerging digital technologies are characterized by layers of contents, services, networks, devices, and the combination of hardware and

software (Henfriedsson, Mathiassen, and Svahn, 2014; Yoo *et al.*, 2010). Therefore, they exhibit the "problem of unbounded causal complexity" (Keil, 2007, p. 1036) with complex hierarchical structures of the mechanisms behind the phenomenon and – consequentially – indeterminate end states of explanation (Rozenblit and Keil, 2002).

As the IOED represents an overestimation of one's abilities to understand a certain technology, we assume that managers who recognize their initial overestimation correct their intention to invest to a greater degree than managers who are not aware of their initial bias. This follows the finding that "the price a person is willing to pay for a financial option is a function of risk" (Frijns, Gilbert, Lehnert, and Tourani-Rad, 2013, p. 2458). The amount a person is willing to invest measures risky behavior (Weber and Hsee 1998), as a higher investment indicates greater (intended) strategic risk taking (Chng and Wang 2016).

We acknowledge that this not measure the actual risk behavior (Reypens and Levine 2018) as there are often gaps in willingness to pay and actual behavior (Nelson et al. 2012). But to measure a change in intention due to the awareness of one's own limited knowledge, a different mindset before and after the re-calibration of knowledge, serves as the closest proxy to come by in an experiment without actual spending the money and buying real companies.

As overestimation of one's knowledge leads to the perception that a specific "situation is less risky" (Busenitz and Barney, 1997, p. 25), we analyze the size of correction in the intention to pay between managers *who were aware of an IOED and those who were not*. The corresponding hypothesis reads as follows:

H1: The recognition of an IOED leads to a stronger correction (reduction) in the intention to invest.

The Visual Self-Calibration of Explanatory Knowledge

Rozenblit and Keil (2002) have already shown that a written (verbal) self-explanation of a phenomenon reduces the IOED and revealed in their study 5 that this was in fact the effect of accurate recalibration and not "a result of feeling "challenged"" (Rozenblit and Keil, 2002, p. 533). Mental representations like a self-explanation enable managers "to see things they were not aware of, and this

insight helps them to define new questions, hypotheses, and models of their data" (Van Wijk, 2005, p. 3). The benefit of self-explanations is also supported by research on learning: "by generating inferences to fill in missing information, integrating new information with prior knowledge, and monitoring and repairing faulty knowledge, learners who self-explain develop more accurate internal representations of a concept" (Kim, Reinecke, and Hullman, 2017, p. 1376). An actively constructed visual representation of knowledge enhances the understanding of one's own uncertainty (Hullman et al. 2018).

Visusalizations structure and externalize original internal or implicit knowledge (Brockmann and Anthony, 2002; Mengis and Eppler, 2006). Visual representations are in fact "more effective than verbal explanations in representing sequential and hierarchical relations" (Guri-Rozenblit, 1988, p. 219). Visual (graphical) support for representations of knowledge leads to a higher accuracy in the understanding of probability distributions (Goldstein and Rothschild 2014). Illustrations allow to show the major components of complex causal patterns and the interaction of these components (Mayer and Gallini 1990) which supports building mental models or mental imagery (Paivio 1969). The provisionality of sketching (Bresciani and Eppler 2018, Hundhausen 2005) creates a "disfluency", an "interruption of the smooth flow of thought" (Ellis, 2018, p. 123). Disfluency makes "people more critical and analytical of that information, allowing for greater consideration of counter-attitudinal arguments, and more skepticism toward attitude-consistent information" (Hernandez and Preston, 2013, p. 179). A more critical analysis of one's own understanding, a deliberate reflection, a deeper computing (Kirsh 2010) should consequentially lead to a better calibration of knowledge, which provides us with the explorative hypothesis 2.

H2: A visual (sketched) self-explanation leads to a more accurate calibration of knowledge (and reduction of the IOED) than a textual self-explanation.

Methods

To test the two hypotheses, we developed two experiments and a coding scheme to analyze the written and sketched (visual) self-explanations of the participants. For the analysis of a potential impact on decisions when people do recognize their IOED, their knowledge limitations in a certain area, we

conducted a second experiment to analyze differences between IOED-calibrated and non-IOED-calibrated participants and their differences in the willingness to invest in a business.

The second experiment consisted of a pre-survey testing for active-open-minded-thinking and 4 experimental steps mainly replicating the original IOED-experiment by Rozenblit and Keil (2002) with the aim of sticking as close as possible to the original setting. To test hypothesis 2, we introduced two randomly assigned modes of self-explanation, a written one and a sketched (visual) one.

Experiment 1

Sample

The participants of the first experiment consisted of 117 managers which participated in international strategy and communication workshops and trainings. They were from 23 different countries (average age 36.98 years, 13.35 years of working experience and 5.72 years of management experience).

Procedure

We let participants watch a video sequence from the Canadian TV show "Dragon's Den" where a start-up called Phazon (focusing on an easy-to-known digital technology topic, wireless earbuds) was presented and one of the investors closed with a concrete offer for the whole company (4 million dollars - the external investment anchor in our experiment).

Thus, after watching the video, all experiment participants had to complete an online survey with the following procedure, using a part of Rozenblit and Keil's experiment on the IOED (2002):

1. Question 1: "After having watched the Phazon/Dragon's Den video: How much would you invest in the company? (Answer within a range from 0 – 5 mio $: invest T1)
2. Random assignment to IOED or control group (CG)
3. Question 2 IOED group only: "How well do you understand how wireless earbuds work, please express your understanding on a scale of 1 (no idea at all) to 7 (excellent understanding)." (IOED T1)

4. Question 3 IOED group only: "Explain how wireless earphones work: Now, we'd like to probe your knowledge in a little more detail. Please describe all the details you know about wireless earphones and how they work." (Self-explanation)
5. Question 4 IOED group only: "Now, please rate again how well you feel you understand how wireless earphones work on a scale of 1 (no idea at all) to 7 (excellent understanding)." (IOED T2)
6. Question 5 IOED group only: "After assessing your knowledge about wireless earphones: How much would you invest in the company now?" (Answer within a range from 0 – 5 mio $: invest T2)
7. New information for both groups (IOED and control group – to give the control group a reason for the second time question about the investment proposal): "Now a Phazon manager informs you that the battery life of Phazon's wireless earbuds is equal to the one in competing producers."
8. Question 6, both groups (IOED and CG): "After this new information: How much would you invest in the company now?" (Answer within a range from 0 – 5 mio $: invest T3)

At the end, this led, for the control group, to two investment statements (invest T1, and invest T3, after the newly acquired, but not really relevant, information), and for the IOED group to three investment statements (invest T1, invest T2 after the IOED test, and invest T3, after the newly acquired information) and the measure of the IOED (IOED T1 and IOED T2, after the written self-explanation). This procedure allowed us to compare invest 1 and 3 for the group without an IOED intervention, the group with an intervention but no correction (correct self-evaluation or stable overestimation) and the group with intervention and correction, to both check for the influence of an IOED on the correction and a potential order effect.

Experiment 2

Sample

For the second experiment, we have enlisted a total of 78 participants, of which 59 were experienced managers (age 30+) who had enrolled in management seminars and workshops as well as experienced

professionals enrolled in different MBA programs (age 25+, 19 participants). Regarding participant demographics, the mean age of all 78 participants was 38.3 years, with 15.0 years of work experience and 8.1 years of management experience. 56 were males, while 22 were females. They came from 11 different countries (a majority from European countries) and covered more than 15 different industries.

Procedure

Pre-Survey: As indicated by Alter et. al. (2010) and Silk-Eglit and Kurtz (2011) cognitive dispositions may have an influence on the degree of an IOED adjustment and one's ability to self-calibrate. Thus, we have integrated a test for the "active-open-minded-thinking" (AOT) as a pre-survey before the experiment to check for variations in the IOED based on the AOT results. To optimize the duration of the experiment and keep it under 30 minutes (as we did the experiments during time-critical seminars and workshop with managers), the AOT-version of Svendholm-Häkkinen and Lindeman (2017) was used. The research of Czerwonka (2017) and Toplak, West and Stanovich (2014) both show that cognitive abilities predict the impact of an anchor bias and therefore a high AOT-rating should lead to a more accurate first self-assessment in explanatory knowledge.

Step 1 – Calibration: To indicate their level of understanding, the participants learned to use a 7-point scale to rate their understanding (deep, partial, shallow) of complex causal patterns on two training examples (the understanding of the concepts of ROI and GPS – the second example was taken from the original experiment).

Step 2 – Measure T1: The participants rated their *level of understanding* (T1) of seven digital technologies. We have chosen these seven key digital technologies as they were mentioned by Forbes as key digital trends (https://www.forbes.com/sites/danielnewman/ 2017/09/26/top-10-trends-for-digital-transformation-in-2018/#42fc2926293a). These seven technologies are generally considered to have a major impact on strategic decisions for a company. In fact, they are consistently cited in various publicly accessible management publications and websites as the key technologies relevant for business today. They are: artificial intelligence, blockchain, internet of things, 5G mobile communication, virtual reality,

augmented reality, and big data analysis. Thus, it could be expected that today's managers are aware and have a certain understanding of these technologies and how they affect their business model.

Step 3 – Measure T2: For three of these technologies (following the design of the original experiment by Rosenblit and Keil), each of the participants was asked to deliver a self-developed explanation (how does this technology work?). The participants were randomly assigned to one of the two mode conditions: 50% of the participants had to deliver a written explanation, while the other 50% of the participants had to create a sketched explanation. After the explanation, the participants re-rated their understanding of all seven items (T2).

Step 4 – Measure T3: For each of the three technologies where a self-explanation was requested, the participants were asked a detailed "diagnostic question" (e.g., how is a crypto currency built and what makes it work?) which they had to answer in writing (for both conditions). Then all participants re-rated their level of understanding for all items one final time (T3).

At the end of the experiment, all participants had to complete a short questionnaire about their background (age, gender, work experience, managerial experience, industry, country of origin).

Thus, every participant rated his or her understanding of the seven digital technologies three times: T1 (the original self-rating), T2 (the self-rating after a visual or written explanation of the phenomenon given by them), and T3 (the self-rating after a diagnostic question concerning the phenomenon and their own written answer).

The Coding of the Self-Explanations (Textual and Visual)

To check for the accuracy of the correction after visual self-explanation, we had to analyze and code the quality of the self-explanations (both textual and visual and both experiments). To do so, we have developed an averaged reference for the self-explanations for the item in experiment 1 and for the three selected items in experiment 2 based on publicly available and easily accessible sources. This reference shows what a manager (rather than an expert in this area) could reasonably be expected to know about wireless earbuds (experiment 1) and blockchain, internet of things, augmented reality (experiment 2). This allowed us to rate all self-explanations in both experiments for completeness of the self-explanation in

comparison to an (authoritative/validated) averaged reference for visual and textual explanations of the technologies.

Coding the textual self-explanations

For an objective analysis of the textual self-explanations ("short free-text answers") a semantic analysis based on the matching of patterns (concept, key words and terms for the item) was applied (Roy et al. 2015). Semantic text similarity (Dijkman et al. 2011) provides a reliable measure of knowledge (Rehder et al. 1998). The correct, item-related key words or terms included in the textual self-explanation (ranging from short essays to even shorter lists of keywords) were counted and compared to an averaged reference (pattern matching). This leads to the following metric for the textual self-explanations:

C(t) = completeness of the textual self-explanation in comparison to an (expert-based/authoritative/validated) averaged reference

T(t) = number of correct, item-related terms/concepts/key words in the text in comparison to an averaged reference

$$C(t) = T(t)$$

Coding the visual self-explanations

For an objective analysis of the visualizations, a metric to quantify the quality of the sketches is a necessity. Literature on metrics for sketches provides different approaches. Ways to code sketches are based on the perceived skills and quality (Booth et al. 2016, Camba et al. 2018, Yang and Cham 2007), complexity and size (McGown et al. 1998), the medium used (McGown et al. 1998, Song and Agogino 2004), representation and annotations (Lau et al. 2009). Joshi and Summers (2012) and Dinar et al (2016) both provide an overview on different metrics to evaluate sketches. For our research, we needed a metric that allows a conclusion for the degree of knowledge revealed about a specific item. In this context, the metric completeness, representing the relevant content via number of data elements (Freitas et al. 2002) is the most useful one. For the visual self-explanations there are two major data elements to code: (correct, item-related) annotations ("type of support notation including labels, lists, narratives, dimensions, and calculation" (Song and Agogino, 2004, p. 352)), and number of (correct, item-related) elements or

artifacts of the item (variety of description) (Grenier 2008, Shah et al. 2003, Westmoreland et al. 2011). The use of annotations (labels) and structure (elements) to measure similarity (or difference) to analyze visual models is also supported by Dijkman et. al. (2011). This leads to the following metric for the visual self-explanations (the visual representations of knowledge) in our experiments:

C(v) = completeness of the visual self-explanation in comparison to an (expert-based/authoritative/validated) averaged reference

A(v) = number of correct, item-related annotations in the sketch in comparison to an averaged reference

E(v) = number of correct, item-related visual elements (boxes, symbols, connections, etc.) in the sketch in comparison to an averaged reference

C(v) = Mean (A(v), E(v))

Both dimensions (A(v), E(v)) can be counted and then compared to the averaged reference value for both. This leads to an objective, explicit, quantitative and manual coding of the visualizations (Dinar et al. 2016, Joshi and Summers 2012).

Authoritative averaged reference

For the comparison of the results with what could be expected to know from a manager we developed an authoritative averaged reference. How good were the participants really, what do they know compared to what could be known? The closest proxy to come by for the expected knowledge of average managers in all kinds of companies. This served as the averaged reference of completeness (C(v or t) = 1.0). This served as the basis to measure similarity (or difference) and thus the degree of completeness for each self-explanation (visual and textual). For this averaged reference we took three visual and short textual explanations for each of the three items tested from public online sources (experiment 1) and three short textual explanations for experiment 2, easily accessible for managers around the world. These show what a manager (and not an expert in this area) could easily know about blockchain, the internet of things, augmented reality, and wireless earbuds with a short Google search. The nine visual explanations were then coded for correct, item-related annotations/labels (A(v)) and correct, item-related visual elements (E)(v), leading to an averaged A(v) and E(v) resulting in the averaged reference completeness C(v). Same

procedure, but with the semantic analysis leading to T(t), for the textual self-explanations, providing the averaged reference C(t) (see details and sources of the authoritative averaged references in the online supplemental material).

Coded groups

The self-explanations and the self-assessments of all participants for both experiments were then coded and categorized. This helped us to compare the initial estimations of knowledge with the "real" knowledge of the participants and the result of their self-calibration after the self-explanations, as testing the real knowledge of the participants in advance would have flawed the experiment. The resulting groups are different combinations of accuracy and confidence levels, pre- and post-experimental. We coded the self-explanations and the self-assessments of all participants according to the scheme below:

Completeness (of self-explanation): < .33 = Low, .33 - .66 = Medium, > .66 = High.

Self-Estimation (of one's knowledge) T1: 1, 2 = Low, 3, 4, 5 = Medium, 6, 7 = High

Self-Estimation (of one's knowledge) T2: 1, 2 = Low, 3, 4,5 = Medium, 6,7 = High

Correction T1T2 (between the two self-assessments): negative, 0, positive.

This led to following ex post grouping of the quality of self-assessments in relation to the completeness of the self-explanations, reflecting Pillai's calibration/miscalibration matrix and its combinations of accuracy and confidence (Pillai 2010):

- OE (stable overestimation – consistent miscalibration): T1 (low, medium, high) > C (low, medium, high), T1T2 = 0, negative, T2 > C
- Still OE (light correction, but still OE – corrected, but still miscalibration): T1 > C, T1T2 = positive, T2 > C
- Overcorrected OE (corrected, but still miscalibration): T1 ≥ C, T1T2 = positive, T2 < C
- OE corr (OE corrected – corrected calibration): T1 ≥ C, T1T2 = positive, T2 = C
- UE (Underestimation – consistent miscalibration): T1 < C, T1T2 = 0, positive, T2 < C
- UE corr (UE corrected – corrected calibration): T1 ≤ C, T1T2 = negative, T2 = C
- Overcorrected UE (corrected, but still miscalibration): T1 ≤ C, T1T2 = negative, T2 > C

- Still UE (light correction, but still UE – corrected, but miscalibration) : T1 < C, T1T2 = negative, T2 < C
- No C (no correction – consistent calibration): T1 = C, T1T2 = 0, T2 = C, correct self-assessment

Results

Experiment 1

As can be expected, the *initial* investment proposal from both groups (with and without an IOED check) in the second experiment (IOED (n=56): 1'946'429$, control group (n=61): 1'850'000$) did not show a significant difference. To analyze the *effect of a recognized IOED on the intention to invest,* we coded the results according to the textual coding scheme. Of all 117 participants, 61 were in the first (control) group without an IOED check, therefore no coding was applied. In the second group, with the IOED check questions, 32 participants made no correction after their self-explanation (due to a correct self-evaluation from the beginning or a stable overestimation), while 24 participants corrected their self-evaluation of knowledge. The repeated-measures ANOVA showed a *significant difference between the adjustments of the intention to invest* ($F(6/110) = 4.28$, $p = .006$). The correction of the group "Overestimation corrected" (n=9, correction = 1'572'222) was significantly different than the other corrections, confirming hypothesis 1 (differences of adjustments per group, see fig. 1).

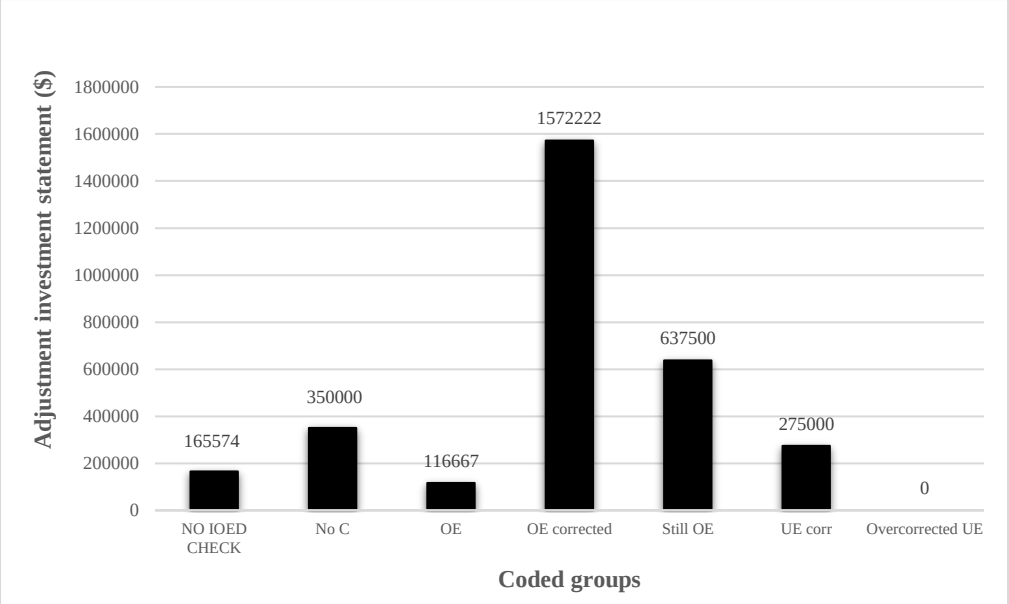

Figure 1: Coding of the groups after the self-explanation: No C: no correction; OE: still overestimation after self-explanation; OE corrected: successful recalibration after self-explanation; Still OE: correction after self-explanation but still overestimating one's knowledge; UE corr: successful calibration of an underestimation; Overcorrected UE: an overcorrected underestimation; NO IOED CHECK: Control group without self-explanation

Existing research has already emphasized and shown order effects (recency and primacy effects) in belief-updating (Hajaj, Hazon, and Sarne, 2014; Hogarth and Einhorn, 1992; Jasper, Kunzler, Prichard, and Christman, 2014; Johnson, 1995; Kwak and Huettel, 2018; Tubbs, Gaeth, Levin, and Van Osdol, 1993; Wang, 1998; Yankova, 2015). We thus checked whether the change in strategic intentions is due to an order effect based on the experimental procedure or indeed provoked by the re-calibration of knowledge. In other words: Do managers with a recognized IOED reduce their intended investment because of the IOED effect or just because of an "simple" order effect by being repeatedly asked the same question?

If the correction of the investment intention for the IOED group is due to an order effect and not because of the recognition of an IOED, then there should be no significant difference in the adjustment of the investment intention between those who corrected their initial rating and those who did not. And there should be a significant difference between the IOED group and the control group, as the IOED group was asked an additional time for their willingness to invest, the repetition of the same question. To check for such an order effect, we split the IOED group in those who recalibrated their knowledge and those who did not (due to correct self-evaluation or a stable overestimation) and compared their final investment

propositions (I3) with those from the control group. The repeated measures ANOVA showed a *significant difference* between the results of the three groups (F(2/114) = 7.69, p = .0007) – see figure 2. The comparison within the IOED groups (corrected vs. no correction of IOED) showed a significant difference in I3 between the two groups (ANOVA, F(1/54) = 7.46, p = .0085), again indicating a strong IOED effect differing from an order effect.

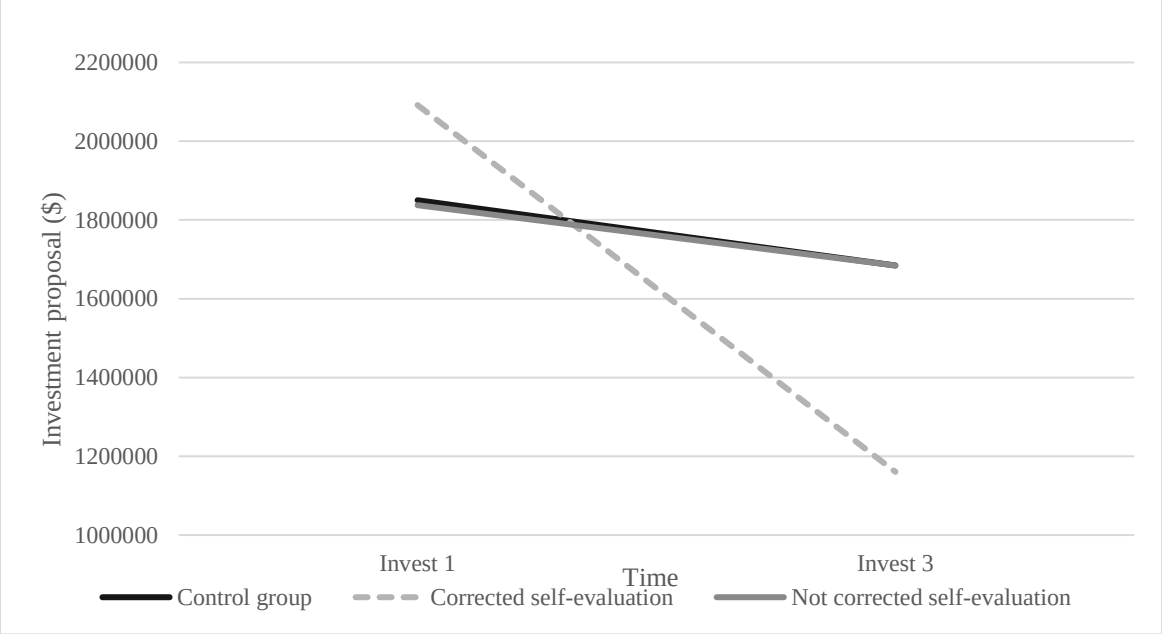

Figure 2: Control group: invest 1 = 1'850'000, invest 3 = 1'684'426; corrected self-evaluation: invest 1 = 2'091'666, invest 3 = 1'160416; Not corrected self-evaluation: invest 1 = 1'837'500, invest 3 = 1'684'375

The analysis of the IOED correction (adjustment T1T2) and the adjustment of the investment proposal (invest 1 to 2) even showed a significant correlation. The size of the IOED correction predicts the adjustment of the investment proposal in invest 2 (ANOVA: F (1/54) = 5.67, p < .0208). *Thus, the bigger the recalibration of knowledge (self-evaluation) is, the greater the reduction of the intended investment towards a smaller strategic risk.* Recognizing one's illusion of understanding thus clearly has the potential to impact decision making.

Experiment 2

General Findings

The results of experiment 2 are aligned with the predictions of the established theory of IOED in other domains. They are also in line with the argument by Gaviria, Corredor, and Zuluage-Rendón (2016) that the high social desirability of specific knowledge like digital technologies contributes to an IOED (i.e., the fact that managers are supposed to understand digital technologies today). The participants showed a *significant drop in the self-ratings from measure T1 to T3* (means T1=3.38, T2=2.79, T3=2.54, repeated measures ANOVA: F (2/1611) = 31.37, $p < .0001$) thus confirming that *managers originally overestimated their understanding of emerging digital technologies*.

There was the overall observation that a higher rating in the active-open-minded-thinking-test (AOT) lead to a smaller adjustment in the re-rating, as predicted by Czerwonka (Czerwonka 2017) and Toplak, West and Stanovich (Toplak et al. 2014), but this effect is not statistically significant with the exception of the tendency for underestimation for managers with a high AOT. There were no observed variations in the impact of an IOED based on management experience and work experience. The relation between the "actively-open-thinking-test" results and the self-assessment groups showed a significant difference depending on the AOT-results, a stronger active-open-minded-thinking (AOT above 5, on a scale from 1 - 6) leads to a stronger tendency of underestimation (ANOVA: F (9/224) = 2.98, $p = .0023$). The result of the likelihood test (multinominal logistic regression) (AOT $\chi^2(9) = 33.09$, $p < .0001$; result of the other factors: age $\chi^2(9) = 11.41$, $p = .2485$; work experience $\chi^2(9) = 6.28$, $p = .7118$; management experience $\chi^2(9) = 11.95$, $p = .2159$) indicates that it is more likely to underestimate one's own knowledge when you have a high AOT-ratio.

The Promise of Visualizations

The result of experiment 2 showed that a sketched self-explanation (n=40) leads to a significantly *higher* adjustment of the self-rating from T1 to T2 than a written self-explanation (n=38). The pooled t-test for the comparison between the visual and the textual self-explanation showed a p-value of .0324 (mean adjustment: text condition = .49, visual condition= .70). *Managers who visualize their current knowledge are hence more aware of its limitations than those who merely provide a written explanation.*

The contingency analysis for experiment 2 relating the two conditions (text and visual) and the coded groups of self-assessments showed a significant difference ($\chi^2(8, N = 234) = 25.08$, $p = .0015$) of the calibration effect (see table I). To analyze whether the visual self-explanation indeed led to a more accurate calibration, we used two categories of calibration: correct calibration (those results which were correct from the beginning and those which were calibrated correctly), and incorrect calibration (all other results, still over- or underestimating one's knowledge). The result of the one-tailed t-test comparing the effect of the visual or textual condition on the correct or incorrect calibration *showed a significant more accurate calibration for those with a visual self-explanation* (t(232)= -1.66, p-value= .0493).

Thus, the visual self-explanation led to a more accurate calibration of knowledge and to a reduction of overestimation compared to the textual one.

	No correc-tion (No C)	Over-estimation (OE) corrected	Under-estimation (UE) corrected	Over-corrected OE	Over-corrected UE	OE	UE	Correc-ted but still OE	Correc-ted but still UE	Total
Text	31	30	5	1	1	28	1	17	0	114
Visual	38	42	2	2	1	15	11	7	2	120
Total	69	72	7	3	2	43	12	24	2	234

Table I: Contingency analysis experiment 2

Moderation effect of informational complexity

A deeper analysis and comparison of the results of all three items revealed an interesting insight. The contingency analyses of blockchain and augmented reality, showed no significant difference in the calibration effect between the textual and the visual condition. For the internet of things, it showed a significant difference between the conditions ($\chi^2(7, N = 78) = 35.51$, $p < .0001$).

By analyzing the interaction of the two conditions (text/visual) and the three items (blockchain, augmented reality, and internet of things) in relation to the outcome of the self-calibration (correct vs. incorrect) we found a significant influence of item ($F(2)=5.95$, $p= .0030$) and the combination item x condition ($F(2)=3.60$, $p= .0289$). *This shows a moderation effect of the item on the visual condition*.

An explanation for this moderation effect is the difference in informational complexity of the three items. Informational complexity is defined by the degree of element interactivity of domain-specific knowledge, the elements that have to be considered simultaneously (Sweller 2020). Complex knowledge is specified by "the number of [information] chunks and their intensity of interaction" (Sorenson, 2005, p. 84) as in technologies with an open network structure without a clearly defined beginning and an end (versus the elements of sequential, procedural, process-oriented technologies with fewer and less complex interactions). Due to these interactions the replication of complex knowledge is harder (Sorenson 2005). As a consequence, the transformation of verbal information into pictorial information of knowledge with a higher informational complexity requires more cognitive resources and as a result facilitates the process of an "external quality control" of one's mental model of understanding a certain technology (Leutner, Leopold, and Sumfleth, 2009, p. 285). The items blockchain and augmented reality are both process-oriented technologies that can be explained with sequential and procedural elements. In contrast, internet of things is more an open network structure with many "chunks" and a high intensity of interaction between. Thus, the higher informational complexity of the item internet of things may impede the visual replication and thus lead to a higher impact of visualization for the calibration.

This means, among other things, that whenever managers are discussing issues with a high informational complexity, they should make a special effort (beyond PowerPoint bullet points) to use interactive, live visualization in their deliberation to avoid an illusion of understanding.

Further Findings

The self-assessment of managers' understanding of digital technologies and the comparison of their knowledge externalized in visual and textual self-explanations with a publicly available averaged reference provided further interesting results (all based on the second experiment):

a) For all three explained technologies the completeness (C) was low (< .33), with an overall mean of C = .24 (blockchain, C = .24; internet of things, C = .31; augmented reality, C = .16) showing a surprisingly modest knowledge of digital technology by our sampled managers.

b) A regression analysis for experiment 1 comparing "completeness" of the self-explanations with the age of the participants showed that *younger managers have significant more knowledge about these technologies* than older ones (ANOVA: F (1/232) = 9.13, p = .0028).

c) A contingency analysis relating gender and the self-evaluation groups showed a significant distinction between *male and female self-evaluation and re-calibration* (χ^2(8, N = 234) = 26.05, p = .0010): *Men tend to keep their overestimation of understanding digital technologies and correct their initial view less than women,* confirming the gender gap in overconfidence (Barber and Odean 2001, Bengtsson et al. 2005, Buser et al. 2020) (see table II):

	No correc-tion	Over-estimation (OE) corrected	Under-estimation (UE) corrected	Over-corrected OE	Over-corrected UE	OE	UE	Correc-ted but still OE	Correc-ted but still UE	Total
Female	31	17	0	1	0	5	6	5	1	66
Male	38	55	7	2	2	38	6	19	1	168
Total	69	72	7	3	2	43	12	24	2	234

Table II: Contingency analysis experiment 2 for male/female overestimation

Discussion, Conclusion, and Limitations

Discussion

Overall, both experiments have shown the existence of an IOED concerning managers' understanding of emerging digital technologies. The participating managers significantly overestimated their understanding of complex causal patterns, creating a "positive illusion" about their own knowledge. This can lead to flawed decision making in the strategy process.

Thus, the features of explanatory knowledge identified by Rozenblit and Keil mentioned above (such as confusing levels of analysis) seem to be useful predictors for the occurrence of IOED in strategic related topics. Our findings also gives support to the hypothesis by Fisher and Keil that especially

intermediary familiar items lead to an IOED; "perhaps items like these are particularly difficult to accurately assess because they are neither familiar, which would lead to frequent recalibration, nor are they totally unfamiliar, which would lead to appropriate caution."(Fisher and Keil, 2016, p. 1265).

How can managers overcome this "positive illusion" which biases strategic decisions in their practice? The results of our studies show that the *externalization of knowledge*, the visual representation of one's understanding of complex causal patterns in the form of sketches, can help to uncover the IOED and (re-)calibrate this knowledge, even stronger and more accurate calibration than a textual self-explanation.

Generally, the use of external representations (both textual and visual) for mental images supports the reinterpretation and the discovery of omissions of internal representations by an examination (and development) of one's own mental images (Reisberg, 1987, p. 281). "The refinement of patterns" (Anderson and Helstrup, 1993, p. 292), the support of solution-solving by self-explanation (Chi, Bassok, Lewis, Reimann, and Glaser, 1989), "the process of externalization helps to refine and disambiguate ambiguous mental images" (Cox, 1999, p. 353) – to show unknown evidence (Walters, Fernbach, Fox, and Sloman, 2016). Additionally, external representations serve as external memory (Hegarty and Steinhoff, 1997; Reisberg, 1987) or cognitive offloading (Liu and Stasko, 2010).

An explanation for this debiasing and calibration effect of sketches combines three characteristics of self-drawn visualizations: first, the affordances "system topology" and "component behavior" through illustrations (Mayer and Gallini, 1990) – which helps to detect gaps in one's knowledge of complex causal patterns. The advantage of visualization is that "one discovers in the process of drawing some aspects were simply absent from the image" (Reisberg, 1987, p. 289), that "the weak expressiveness of graphics makes inference more tractable" (Cox, 1999, p. 350), even generates and reinforces inferences (Glenberg and Langston, 1992). The second characteristic is the mental disfluency (Ellis 2018) provided by the provisionality, fuzziness, vagueness or small degree of perceived finishedness of self-sketched visualizations (Bresciani et al. 2008, Hundhausen 2005, Platts 2001, Swedberg 2016). The creation of a disfluency promotes metacognitive difficulty and thus leads "to deeper processing of the information and less reliance on heuristic modes of processing. The third characteristic explaining a potential debiasing

and calibration effect of sketches is the cost structure of computation: sketching as fast method to produce an external representation of one's own knowledge reduces the "cognitive cost" of calibration (Kirsh 2010). "Graphical representations such as diagrams limit abstraction and thereby aid processability" (Stenning and Oberlander, 1997, p. 98). This is also supported by research from Larkin and Simon (1987) that in visualizations information is organized by location and needs less computational power to be extracted. These findings contribute to the already mentioned aspects of the higher effectiveness in representing relations (Guri-Rozenblit 1988) and the improvement of reasoning (Bauer and Johnson-Laird, 1993).

Conclusion

The sequence of experiments on the illusion of explanatory depth and visualization adds another perspective to the use of visualizations in strategizing, complementing the "visual turn" in strategy research: Visualizing one's own technology understanding does not only reveal an illusion of explanatory depth as effectively as a textual externalization, but even calibrates the individual knowledge more accurately than a textual one. Visualization thus supports *debiasing* in strategizing, especially for knowledge with a higher informational complexity (as it is often the case in strategic decisions).

Additionally, our research also shows that recalibrated knowledge leads to lower strategic risk taking. Uncovering one's overestimation of understanding digital technologies with sketches or textual self-explanations does not only facilitate a better calibration of this knowledge, but also reduces the intention to take riskier decisions (in domains that one does not understand well). In this context, however, we have to be aware that overconfidence is ambiguous in decision making and "not bad per se" (Thomas, 2018, p. 119) and can even be beneficial (Busenitz and Barney 1997, Grichnik 2008, Koellinger et al. 2007, Rose 2008, Tang et al. 2012) with positive implications. Thus, the application of this finding in strategy practice may depend on the specific situation and decision.

Our further findings section revealed another interesting implication for the current practice of strategizing: it indicated that at times managers' knowledge of emerging digital technologies is quite modest, and that the inclusion of *female and younger managers* combined with *visual* externalization of

knowledge may help to have a more accurately calibrated knowledge as a basis for strategic decisions (and thus increase a management team's propensity to seek advice on such technology by experts).

Limitations

The experiments presented in this study face several limitations. First, they focused on the mode variations text/visual. The form of an oral self-explanation was not examined, neither was the effect of disillusioning (revealing overconfidence in knowledge) in groups in contrast to individual disillusioning. Thus, further research could focus on other techniques and tools of disillusioning than the individual visualization of one's knowledge, as could be an in-depth analysis under which conditions visual methods are more or less effective in adjusting an inaccurate anchor or which kind of visualizations support debiasing knowledge illusions best, as "visualization designs affect decisions" (Xiong, Shapiro, Hullman, and Franconeri, 2020, p. 853).

Second, actual in-situ managerial behavior was not analyzed in our research. Experiment 1 focused on the change in *intention*. We acknowledge that this does not measure the actual risk behavior (Reypens and Levine 2018) as there are often gaps in willingness to pay and actual behavior (Nelson et al. 2012). But to measure a change in intention due to the awareness of one's own limited knowledge, a different mindset before and after the re-calibration of knowledge, serves as the closest proxy to come by in an experiment without actual spending the money and buying real companies. Thus, future research may go one step further and observe how an IOED impacts actual behavior in strategic decision making, as recommended by various scholars (Baumeister et al. 2007, Nelson et al. 2012, Reypens and Levine 2018).

Third, as the original procedure of the IOED experiments showed the difficulty of a "traditional" control group (you cannot check for existing knowledge before the experiment without influencing the results of the self-evaluation), we used the results of the self-explanations compared with an "averaged reference" to control for actual knowledge in both experiments. The choice of this references and their coding is not perfect, and we thus tried to minimize the influence of these subjective choices by categorizing the results broadly (low, medium, high knowledge, for example) and not use a continuous scale.

Fourth, the impact of an IOED has been measured on a simple investment example based on an individual’s choice and not on complex team-based strategic decisions. This lacks the integration of a perspective on variations due to factors like cultural background, group think effects, social desirability bias etc. These issues should be integrated in future research on the phenomenon of an IOED in management.

Nevertheless, the results show that *visualizing what you think you know* is one effective way to improve strategizing that should be further explored in research and practice. In this way, managers who embark on digital strategizing can become, with a little help from visualizations, aware of the limitations of their own knowledge and hence reduce this bias in their strategic decisions.

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