WHEN DECISION SUPPORT SYSTEMS FAIL: INSIGHTS FOR STRATEGIC INFORMATION SYSTEMS FROM FORMULA 1

Paolo Aversa, Laure Cabantous, Stefan Haefliger
Cass Business School, City, University of London

Forthcoming in *The Journal of Strategic Information Systems*

ABSTRACT

Decision support systems (DSS) are sophisticated tools that increasingly take advantage of big data and are used to design and implement individual- and organization-level strategic decisions. Yet, when organizations excessively rely on their potential the outcome may be decision-making failure, particularly when such tools are applied under high pressure and turbulent conditions. Partial understanding and unidimensional interpretation can prevent learning from failure. Building on a practice perspective, we study an iconic case of strategic failure in Formula 1 racing. Our approach, which integrates the decision maker as well as the organizational and material context, identifies three interrelated sources of strategic failure that are worth investigation for decision-makers using DSS and big data: (1) the situated nature and affordances of decision-making; (2) the distributed nature of cognition in decision-making; and (3) the performativity of the DSS. We outline specific research questions and their implications for firm performance and competitive advantage. Finally, we advance an agenda that can help close timely gaps in strategic IS research.

Key words: DSS, affordances, big data, strategic information system, decision-making, distributed cognition, performativity, practice theory, Ferrari, Formula 1.

INTRODUCTION

Decision support systems (DSS), which often process big data using models and output results through multiple interfaces, increasingly pervade knowledge-intensive professions from traffic control, health, to security, and finance (Constantiou & Kallinikos, 2015; Galliers, Newell, Shanks, & Topi, 2015; George, Haas, & Pentland, 2014). Data support strategic decision-making in various ways by feeding models and technologies of visualization and control (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2014; Brynjolfsson & McAfee, 2012; Loebbecke & Picot, 2015; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). Recently, scholars and practitioners have agreed on the bourgeoning importance of DSS and big data for strategic decisions, which—if properly leveraged—can positively contribute to firm performance, profit, growth, and competitive advantage (Davenport & Harris, 2007; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; McAfee et al., 2012). Information System (hereafter IS) research on big data and decision support systems has primarily focused on the technological aspects and design challenges of big data (Chen, Chiang, & Storey, 2012; Chen, Mao, Zhang, & Leung, 2014) and only recently started considering the organizational dimensions of strategic decision-making with big data (Constantiou & Kallinikos, 2015; Günther, Mehrizi, Huysman, & Feldberg, 2017; Poleto, de Carvalho, & Costa, 2015). We argue that the design and use of tools in context deserve more attention given the well-known challenges of modern DSS, particularly when big data further complicate their functioning. This organizational dimension of decision-making builds on the managerial definition of big data and associated challenges (McAfee et al., 2012): (1) Sources of data become increasingly diverse, multiple, and dynamic; (2) More stakeholders in decision-making generate and analyze data using more and more devices; (3) Feedback speed and volume of data favors the non-human actors (e.g., Artificial Intelligence and similar solutions).

In this paper, our aim is to contribute to strategic IS research on DSS by showing the value of considering the organizational dimension of decision-making with big data, in situations that are strategic to a firm’s competitive advantage. To do so, we analyze in detail an extreme case of decision-making with DSS with big data leading to failure of strategic dimensions in Formula 1 (F1): the 2010 Abu Dhabi grand prix where the Ferrari team lost the F1 world championship due to what was considered by many a judgment error in retrospect (Allen, 2010; Collantine, 2010). We choose this event for three main reasons. First, given the clear relation between DSS and performance in F1 and the fact that, in this field, performance and competitive advantage are unmistakably measurable (Aversa & Berinato, 2017; Gino & Pisano, 2011; Marino, Aversa, Mesquita, & Anand, 2015), F1 has been mentioned as an ideal setting for studying the use of big data (George et al., 2014: 321), and it is particularly suitable to observe DSS-aided decision-making under pressure. Second, this decision failure case epitomizes business situations where time is critical and information systems cannot be separated from their context of use, neither in space nor in time. It is therefore an ideal case to shed light on the strategic implications of the design and use of DSS for organizations—which ultimately determine organizations' success or failure. Third, and importantly, this case exemplifies the three challenges of big data and creates inroads into a research agenda in strategic IS with the development of decision-making tools in mind. The development of tools and information technology artifacts is the domain of design science (Hevner, March, Park, & Ram, 2004; March & Smith, 1995) that includes the organizational domain by taking into account the user (Markus and Silver, 2008) as well as the openness of a system that remains incomplete (Garud, Jain, & Tuertscher, 2008; von Krogh & Haefliger, 2010).

In order to analyze this iconic case of DSS with big data under time pressure, we adopt a practice-based perspective (Gherardi, 2001; Nicolini, 2011). This perspective has gained increasing interest both in the IS (Arnott & Pervan, 2014; Cecez-Kecmanovic, Galliers, Henfridsson, Newell, & Vidgen, 2014a; Cecez-Kecmanovic, Kautz, & Abrahall, 2014b; Peppard, Galliers, & Thorogood, 2014) and strategic management (Cabantous & Gond, 2011; George et al., 2014; Jarzabkowski & Kaplan, 2015; Vaara & Whittington, 2012; Wagner, Newell, & Piccoli, 2010; Whittington, 2014) communities over the recent years. As applied to strategic decision-making with DSS, a practice-based approach invites IS scholars to consider not just the individuals who make the decisions (together with their cognition) but instead to study the 'practice of deciding.' In other words, this perspective suggests approaching decision-making as a situated, social and material practice involving the decision-makers, the technologies, and the specificities of the decision contingencies, in order to study how the relations between all these elements constitute decisions and ultimately to evaluate their outcomes (Cabantous & Gond, 2011; Cabantous, Gond, & Johnson-Cramer, 2010).

Our practice-based interpretation of the case leads us to question the public interpretations of the 'heroic' individual user of a DSS who succeeds or fails and we reveal three groups of insights: the first is about the closely connected sets of biases at the intersection of the human and the machine. IT and DSS with big data are not simply at the service of a boundedly rational human decision maker, even if that is the sole public interpretation of the events. A more nuanced analysis of this strategic decision failure reveals the importance of considering decision-making with big data as a socially situated practice, and hence to consider the affordances of IT artifacts and the organizational context. It also shows that strategic decision-making with big data must be understood within a distributed cognition approach; and finally shows the importance of considering the performative power of the models that aggregate and structure the data entering the DSS. Ultimately, our analysis shows the importance of considering decision-making with DSS and big data as a social and material practice given the diversity of uses of decision-making technologies and artifacts in time and space, while paying careful attention to their interpretive flexibility or affordance (Bernhard, Recker, & Burton-Jones, 2014; DeSanctis & Poole, 1994; Junglas, Goel, Abraham, & Ives, 2013; Markus & Silver, 2008; Zigurs, Poole, & DeSanctis, 1988) as well as other intangible aspects such as organizational culture (Barney, 1986; McDermott & O'Dell, 2001; Schein, 1985; Suppiah & Singh Sandhu, 2011).

Overall, our analysis leads to more questions than answers because it invites a reading of the failure case that goes beyond what the press and observers took as a first conclusion in order to stimulate research in strategic IS and systems design. Our analysis also enables us to develop a compelling research agenda for strategic IS scholars, which, in line with recent key contributions (Arnott & Pervan, 2014; Peppard et al., 2014), pays particular attention to the role of recent DSS for strategic purposes, including the interactions between the technical and organizational dimensions of decision-making as a response to the challenges laid out by authors who recently addressed the business promise of big data (Baesens et al., 2014; Davenport & Harris, 2007; Jacobs, 2009; Lazer, Kennedy, King, & Vespignani, 2014; Loebbecke & Picot, 2015; Poleto et al., 2015). We conclude our paper by discussing implications for design science and the management of strategic information systems.

THEORETICAL BACKGROUND

The strategic use of IS in practice can lead to individual and organizational failure, and it is one of the foremost challenges of scholarship to help decision makers and support their potential to make successful decisions (Günther et al., 2017; McAfee et al., 2012). Several key strategic domains in organizations – e.g., those related to business models, innovation, and operations – are strongly influenced by decisions taken with the help of DSS and big data. Advances in technology as well as in the theoretical understanding of the role that material artifacts such as IS play in collaboration and decision-making (Leonardi, 2011; Nicolini, Mengis, & Swan, 2012; Orlikowski, 2000) have led strategy and IS scholars to increasingly study practice as a sight of research (Jarzabkowski & Kaplan, 2015; Mazmanian, Cohn, & Dourish, 2014; Scarbrough, Panourgias, & Nandhakumar, 2015). Fundamentally, this is because the strategic outcome of decisions partly depends on the actual use, *in situ*, of the tools available to the decision makers. The input and models that constitute a DSS are as important as the decision makers who employ them towards a desired outcome, which is why "decision-making 'disasters' may stem from the oversimplification or misrepresentation encoded in tools" (Jarzabkowski & Kaplan, 2015: 538; March, 2006). The affordances of the tools (e.g., DSS, models, screens with visual representations etc.) represent our first point of departure when studying a case of strategic decision failure.

DSS have a long history of taking into account groups of decision makers and the types of tasks they face (DeSanctis & Gallupe, 1987) as well as the processes and approaches of implementing systems in practice (Earl, 1993). Only more recently have scholars called for closer attention to the doing and thinking of individuals and their artifacts (Cecez-Kecmanovic et al., 2014b). In this view on strategic IS, the missing elements include a holistic, integrated perspective rather than different approaches (Earl, 1993): a practice-based approach "prefers concrete micro actions rather than abstract macro analysis (Peppard et al., 2014: 1)". Such a practice approach to decision-making may bring to the fore how and why different uses of tools such as DSS lead to various outcomes and help IS scholars relax some of the prevalent dualities between human and computer, or between thought and action (Feldman & Orlikowski, 2011). Yet, this approach is still not fully developed in strategic IS. This brings us to our second starting point, which considers that cognition is not simply located in the (head of the) decision maker but is distributed across a variety of entities (Boland Jr, Tenkasi, & Te'eni, 1994). We shift the locus of decision-making for strategic purposes from the mind of the individual(s) making the decisions, to the network of artifacts and human beings involved in the practice of deciding. Approaching cognition and decision-making as a distributed phenomenon (Hutchins, 1995b, 1995a) can help strategic IS scholars to better understand how the specificities of the decision situations, as well as the relations and entanglements between human (e.g., decision makers) and non-human (e.g., models, screens, software, remote partners) entities shape decisions with DSS and big data. It also brings into the picture the importance of organizational culture as background contingency affecting ex-ante the decision process design, and ex-post the interpretation of the outcome (Barney, 1986; Schein, 1985).

A third point of departure is equally rooted in long-standing thinking about strategic IS, namely the status of belief in policy and the role of "semi-confusing information" (Hedberg & Jönsson, 1978). According to Hedberg and Jönsson (1978), the embedded rules and models within an IS can stabilize or destabilize organizational action and, therefore, its outcomes, and competitive advantage. The appropriate triggers for change can be located in the use of semi-confusing information feeding into the models that organizational actors trust or follow. Thus, in response to the increasingly prominent role played by models and artificial intelligence today, a practice approach is well suited to reveal the performative dimension of strategic IS. Performativity studies focus on the transformative power of models, seen as intermediary devices between theory and reality (or myth and environment, in Hedberg & Jönsson, 1978), in shaping practice, and document the feedback loops between reality and the models embedded in these tools (Callon, 1986; MacKenzie & Millo, 2003). Models—like those embedded in DSS—are (imperfect) "representations" of the real world, and actors use them to model and change the reality (Morgan, 2012), so that their nature and enactment shape reality itself in a recursive way. Approaching decision-making from a practice perspective could help IS scholar better understand how advanced DSS, which are "models" that integrate both expert knowledge of IS engineers and the knowledge of the users, are used and manipulated and, ultimately, how the models embedded in the tools play an active role in decision-making.

In summary, we approach strategic decision making supported by IS from a practice perspective that borrows from pivotal work combining strategy-as-practice with IS research (Arnott & Pervan, 2014; Peppard et al., 2014; Whittington, 2014). Specifically, we probe a critical case of strategy failure because, theoretically, such a case may reveal the challenges for the design of IS in high resolution due to the collapse of a routine event: multiple actors interpret, *ex post*, what went wrong and reflect intensely upon the sources of failure, not least because of the dramatic costs for the organization (in our case, Ferrari's underperformance). Given the proposed focus on the use of tools in context (Jarzabkowski & Kaplan, 2015) and on episodes of strategizing (Whittington, 2014), we analyze the causes of failure in detail starting from three salient issues that appear in traditional research on DSS and dominate a practice perspective today: affordances, distributed cognition, and performativity. Our effort aims to synergistically continue the route clearly identified by recent contributions (Arnott & Pervan, 2014; Peppard et al., 2014) towards an integrated perspective that foster an holistic views of the critical use of DSS, particularly when the combined effect of big data and pressuring conditions favor erroneous use and highlight systematic pitfalls related to strategy design and implementation.

METHOD

Empirical setting

Our contribution is grounded in events happening in a competitive setting that is ideal to observe causes and effects of decision-making with big data: the last race of 2010 Formula 1 World Championship, taking place in the UEA, Abu Dhabi Grand Prix (Yas Marina racetrack). In this occasion Ferrari's driver Fernando Alonso unexpectedly lost the F1 Driver World Championship due to what media and field experts unanimously have defined as its team's mistaken 'race strategy.' Such strategy was driven by a modern DSS system that heavily relied on big-data (Collantine, 2010).

A F1 team's most evident strategic objective is winning car races of the F1 World Championship, thus obtaining the best performance within the season and maximizing the income derived from superior race performance (mostly through monetary prizes, increasing sponsorship, and enhanced global visibility). Every year, the *Fédération Internationale de l'Automobile* (i.e., FIA), which is the governing body that rules the sport and the industry, allocates the revenues with the F1 teams on a proportion of their race results. Accordingly, most of the teams' efforts and investments are aimed at improving the technological performance of their cars on the racetrack, and thus their sport achievements—which are fundamentally correlated (Aversa, Furnari, & Haefliger, 2015; Sylt & Reid, 2010).

F1 cars are incredibly complex vehicles whose architecture reaches its performance peak only when the combination of its parts is perfectly balanced (Marino et al., 2015). During the race, this architectural balance is obtained through an ad-hoc set-up conducted by the engineers in the pits before the race and by the drivers based on the instruments available in the car cockpit during the race. Each driver can adjust several parameters such as movable wings, suspensions, engine mapping, weight ballast, and breaking distribution to optimize the functioning of their car. All F1 cars use special high-performing tire sets that are available in different compounds and designed to better perform under different weather conditions (e.g., dry, semi-wet, wet race etc.). As tire sets deteriorate rapidly through the race, F1 teams can call their cars to the pit-lane in order to change the worn tire set with a set of fresh ones. Today, a tire change called in technical jargon “pit-stop” (Leslie, 2015), involves 20 people performing 34 actions in around 2.3 seconds, but overall each car spends between 20 and 30 seconds in driving through the pit lane, changing tires, and getting back into the action of the racetrack (i.e., in technical jargon this is referred as ‘pitting’ the car). Teams can perform several pit-stops per race (usually between one and four depending on the specific race and tire characteristics).

Defining the number and timing of pit-stops are two of the most critical decisions for a team during a F1 race. Teams’ decisions vary massively on both aspects and they determine success and failure in races. To monitor, analyze, and deploy the best strategy during a race (vis-à-vis current conditions and competitors’ strategy), each F1 vehicle combines advanced telemetry systems with a complex modeling simulation (Bi, 2014). Telemetry in F1 is the transmitting of streams of live data sourced by racing car sensors—there are between 160 and 300 on each car—generating between 1 and 20 gigabyte of data in each race. The output is sent (often through a proprietary wireless protocol based on around 800 channels) to each team’s data elaboration center in the racetrack pits and simultaneously rebounded to the “remote garage” back in the company headquarters in Europe. There, a team made of up to 30 engineers and IT specialists runs simulations that forecast the possible race outcome given the current car’s data (i.e., race performance, activity of the subparts, and drivers’ biophysical data etc.), the relative position of the other cars on the track and their most likely race strategy as well as a variety of other factors. The models that are used to run these simulations are based on assumptions that derive from the team strategists’ experience, as well as historical data from previous races—about 60% of the data generated by the car is used in that race, while the remaining 40% is stored for later applications. The outcome of this modeling is a selected portfolio of strategic options that is sent back to the ‘race pitwall’ (i.e., the data analysis center at the racetrack), where the chief race strategist has only a few minutes to cross check the selected strategic options with the data in his control displays, consult with the race engineer in charge of the team’s cars, and make a decision—such as ‘to pit’ the car, wait until a later lap, or not pitting at all.

[Insert Figure 1 about here]

The complexity of this process and the incredible (time) pressure during the racing competition push most of the companies to hire entire teams of IT specialists for data telemetry and data analysis and to spend around 5% of their yearly budget—which is between $150 and $500 million per year—in developing a high-performing and reliable real-time DSS with big data. F1 championships are won or lost partly because of this process and the events and practices in racing represent a promising arena for research in strategic IS both due to the fast-paced decision practices and due to the ongoing development of tools that support strategic decisions under high pressure.

Data collection

The secrecy of the F1 world, the risk of retrospective call biases, and the limited number of acknowledgeable informants to report on such iconic events represent a major challenge for information collection in this setting. Despite this challenge, we nonetheless managed to conduct a series of exclusive semi-structured interviews with some of the (very few) people directly involved with this strategic decision, namely F1 executives Chris Dyer (Chief Race Strategist at Ferrari—in charge of calling the final pit-stop strategy), Piergiorgio Grossi (Chief Information Officer at Ferrari—who supervised the design and implementation of the DSS), and Otello Valenti (Head of HR at Ferrari—in charge on inquiring on the team's responsibilities after the race). These interviews aimed at gaining details and granularity of the decision-making context, including information on the sequence of events, the nature of the DSS, the support technologies, and the types of data used, as well as the interaction between human and technological agents. We also inquired about Ferrari's organizational and decision-making culture. In order to complement out 'off-the-record' account of the race, we also interviewed three F1 journalists who oversaw the race from the media box above the pit-lane. In our interviews with journalists, we covered similar topics as with the executives, but we also inquired about the rumors, 'paddock talks' and the actions not reported by the media. All in all, the interaction with our six expert informants accounted for an average of 2.5 hour each, for total of 18 hours of engagement. The interviews were recorded, transcribed, and analyzed in conjunction with the archival sources. As we were concerned for the small number of informants, we asked F1 professionals whether other people should have been considered as acknowledgeable informants, but were told that the few people we had met were those who had made the decision, and no-one could have provided a more fine-grained report of what exactly happened.

We complemented this unique set of interviews with publically available real-time information about the race. As per usual F1 rules, all communication during the race happens via radio and the communication with the driver are recorded and available for research purposes, while the communications between the team members is owned by Ferrari, and are not accessible. We therefore collected the official Ferrari driver Fernando Alonso communication with the Chief Race Strategist at the pitwall (Chris Dyer).

Finally, in order to have the most comprehensive interpretation of the sequence of events and attribution of responsibilities for the (failing) decision at Ferrari, we searched the media database Factiva for all sources (e.g., newspapers, blogs, etc.) in English language published about the focal event (Siggelkow, 2007) two weeks before and up to one year later. Keywords like "Abu Dhabi," "UAE," "Grand Prix," "Yas Marina," "F1," "Formula 1," "Ferrari," "Alonso," where combined in multiple forms to retrieve the documents. We ultimately retained 52 documents (around 120 pages) out of the 356 documents that the search returned[1]. These documents include interviews taken close before, during, or right after the event—which partially reduces concerns for retrospective call biases, and contain detailed opinions and interpretations from key stakeholders such as Ferrari's President, Ferrari F1 team CEO, Ferrari's Technical Director, FIA's president, other drivers, engineers, mechanics, technicians, Formula 1 journalists, and fans.

Data analysis

Our analysis was aimed to identify the factors that played a significant role in determining Ferrari's race strategy and its unsuccessful turnout. Following standard practices in grounded theory (Strauss & Corbin, 1990), two scholars intimately familiar with F1 (both from an industry as well as academic perspective) discussed the materials and reconstructed the sequence of events and decisions using tables and schemes. We leveraged a set of the most significant quotes from the event protagonists to enhance our descriptive narrative of the events. Then, we adopted a systematic approach to concept development and grounded theory articulation, by focusing on aggregating the available evidence to identify a set of explanatory constructs (Gioia, Corley, & Hamilton, 2012a). Moving from *first-order concepts* (i.e., evidence from the field such as individual "Overconfidence biases", "Attention bases issues") we identified *second-order themes* at a higher level of abstraction (e.g., "Cognitive biases"; "Factors enhancing cognitive biases") and ultimately *aggregate dimensions* that point to specific theoretical perspectives (e.g., "Individual bounded cognition"). In this process, a third scholar (less familiar with the setting) acted as devil's advocate (Gioia, Corley, & Hamilton, 2012b: 19; Van Maanen, 1979) and challenged the interpretation and aggregation results. Questionable interpretations were discarded. Finally, following commons visualization practice (Corley & Gioia, 2004), we built a table reporting the data structure (see Table 2). As we analyzed the data, we carefully searched for explanations and justification of the decision, and tried to disentangle the chain of causes that determined the final outcome, particularly when this was grounded in the contingencies that affected the decision. We also aimed at separating the opinions from the media and the public, while comparing them to the evidence we collected from the field and from the interviews with the protagonists.

DECISION SUPPORT SYSTEM FAILURE: OBSERVATIONS FROM FORMULA 1

Chronicle of the race: F1 Ahu Dhabi grand prix 2010

On Sunday November 14th 2010, the German driver Sebastian Vettel crossed the finish line of the Grand Prix of Abu Dhabi as first, and gained the Formula 1 World Championship on a Red Bull Racing car. This moment became a memorable event in the history of F1 as it represented an

[1] All materials are available upon request, including videos of the race and audio commentaries

unprecedented case on many aspects. It was the first time Red Bull Racing won the F1 World Constructor's Championship; the first time Sebastian Vettel won the F1 Driver's Championship; and the first time that Formula 1 raced in Abu Dhabi, UAE. In addition, the results of the race came rather unexpected: Before the Abu Dhabi's showdown the Driver's Championship ranking had been dominated by Fernando Alonso of the Ferrari team (246 points) followed by Mark Webber of Red Bull Racing team (238 points), while Sebastian Vettel followed in third position (232 points). Vettel had performed very well throughout the weekend, obtaining the best lap during Saturday's qualifying session, and thus the pole position in the starting grid for the Sunday's race.

However, the media and the public opinion unanimously agreed that him winning the world championship would have not been possible without a key strategic mistake made by the Ferrari team, which unequivocally compromised not only Alonso's race but also his possibility to win the F1 Driver's World Championship title (see among others interpretations by Allen, 2010; Collantine, 2010). Even in the case of Vettel's victory of the Abu Dhabi grand prix, Alonso would have been able to maintain the top spot of the championship tally—and thus graduating F1 world champion—by finishing in 4th place; and yet the team's decision in an early pit-stop timing "contrived to lose him positions so he ended up seventh" (Allen, 2010). Table 1 shows the participants and the final ranking at the end of the 2010 Abu Dhabi race.

[Insert Table 1 about here]

At the 2010 Abu Dhabi race, Ferrari's strategy was in the experienced hands of the Australian Chief Race Strategist, Chris Dyer. Despite being the first time ever that a F1 grand prix was taking place at Yas Marina Circuit in Abu Dhabi (UEA), Chris Dyer could count on his long experience in F1 that started in 1997 with Arrows and continued since 2001 at Ferrari where he had significantly contributed to winning five World Championships with Michael Schumacher (one of the most successful drivers in F1 history) and one championship with the Finnish driver Kimi Raikkonen. The DSS used by the Ferrari team at the 2010 Abu Dhabi race was one of the finest and most advanced in the entire F1 circus: a Monte Carlo simulation model with deterministic parameters designed by the Ferrari IT department under the coordination and supervision of Piergiorgio Grossi, at the time Ferrari's Chief Information Officer.

At the very first lap the driver Michael Schumacher (Mercedes team) had an accident that stopped his car and forced him to retire. As often in these cases, to help officers safely clear the tarmac from the broken car and its debris, the 'safety car' was called out to the track and all F1 cars slowly proceeded in line behind it until works were completed and the track was restored. During this time, some mid-field cars pitted. Alonso had started the race in third position and was quickly overtaken by McLaren's driver Jenson Button in the first lap, while Mark Webber (2nd in the championship) maintained his 5th position from qualifying. With Sebastian Vettel leading, it was imperative for Alonso to keep his 4th position, or the difference in points gained would make Vettel win the championship. In this context, it was Mark Webber (5th position) who represented the biggest threat for Alonso. Ferrari head strategist, Chris Dyer, thus mainly based Alonso's strategy on Webber's moves. Relatively early in the race, at lap 11 of 55, Webber's car experienced rapid tire degradation and was called to the pits to substitute his worn tire set with a fresh one. In order to maintain the gap with Webber, Ferrari Chief Strategist 'pitted' Alonso soon after Webber (lap 15 or 55). The outcome of this pit-stop decision was aimed to make Alonso come out of the pit lane in front of Webber, but in 12th position, behind drivers who had not pitted yet.

To make Alonso end up in the desired 4th position, Ferrari's team was assuming Alonso to be able to overtake the cars racing in front of him. Alonso had in fact a competitive driving style, with particular skill in overtaking, and his Ferrari had a much quicker pace than the cars ahead. However, the Abu Dhabi racetrack characteristics were making overtaking very difficult for all cars, and indeed very few overtakes had happened until that moment. Alonso surprisingly got stuck behind other less performing cars such as the Renault driven by Vitaly Petrov. To win the championship, Alonso could afford to leave only Vettel and other three competitors in front of him but his early pit had laid another four cars ahead of him—two of which (Vitaly Petrov's Renault and Nico Rosberg's Mercedes) had already pitted opting for a single pit strategy, and thus would not be stopping again; while others more ahead were able to pit and still re-join the race in front of Alonso. As a result, Alonso finished his race in 7th position, thus concluding the F1 Driver's World Championship in 2nd place with only 1-point difference from Sebastian Vettel.

Post-race analysis highlighted how this outcome could have been reverted, had Chris Dyer decided not to pit Alonso right after Webber. All other things equal, had Ferrari left Alonso out and called him to pit around 20 laps later than when he pitted, the situation would have allowed Alonso to rejoin the race in 4th position and win the world title (Allen, 2010).

Media and public interpretation

[Insert Table 2 about here]

All the secondary sources and expert opinions we retrieved converged in attributing to the *individual bounded cognition* of the decision maker (Ferrari's Chief Strategist Chris Dyer) the main responsibility for the negative result (see the 1st aggregate dimension in Table 2). Heads at Ferrari identified the decision to pit Alonso at lap 15 as the critical error, and ultimately blamed Chris Dyer who made that strategic call.

> *"We made a wrong decision in terms of strategy (...) we were unduly concerned about the wear rate of the soft tires and we did not take into consideration the difficulty of getting past other cars on the track." Stefano Domenicali, Ferrari F1 Team Principal (Allen, 2010)*

External experts also agreed in identifying this a key strategic mistake by Chris Dyer:

> *"Ferrari snatched defeat from the jaws of victory in Abu Dhabi. Fernando Alonso's race hinged on a critical strategic decision to pit early, which left him stuck behind Vitaly Petrov."*

Keith Collantine, Editor at F1Fanatic.com (Collantine, 2010)

Media mentioned, directly or indirectly, several cognitive biases, including Chris Dyer's switch of attention from achieving the actual goal (ending the race in 4th position) to out-racing the closest competitor (Mark Webber, which in the end represented a minor threat compared to Sebastian Vettel). For example, an expert informer wrote:

> *"The reason they made the mistake was because they were too concerned with what Mark Webber was doing and failed to see the bigger picture." James Allen, F1 Editor at Financial Times (Allen, 2010)*

Media also blamed Dyer's overconfidence, and his overly optimistic belief that his driver (Alonso) could successfully overtake the cars in front. This is probably motivated by the fact that Fernando Alonso was one of the best drivers in overtaking, held the highest number of points at the beginning of the race, and was racing with a very quick car. Also, Ferrari was aware of its proficiency in DSS with big data development, compared to the other competitors in F1. Other key factors were pointed out as to enhancing the negative effects of such cognitive biases: For example, time pressure during the decision—there were only few minutes and laps to ultimately decide whether to pit or not—and task overload, as there were many different technical tasks that Dyer had to perform during the racing weekend and his Chief Strategist role was not seen as a "full-time" activity. Experts claim that Dyer made a decision

> *"…[that] was wrong not because of a bug (in the DSS), but because of the settings and the probabilities and so on. What I think is that with a different pressure, with more people looking at it, or focused mindset, probably it was not so difficult to understand that the software was wrong and there was something else to do. I am sure that Chris at home, without any data would have not called the driver in. He was kind of distracted." Piergiorgio Grossi, Head of IT at Ferrari (interview, 2015).*

Finally, field evidence suggested that the novelty of the race (it was the first F1 race ever in Abu Dhabi), and Dyer's limited personal experience in that specific track might have biased his decision and underemphasized the challenges in adopting a race strategy mostly based on overtaking.

After debriefing on the race result, Ferrari executives decided to fire Chris Dyer, which terminated his involvement in F1 for 6 years (as in 2016 he came back to F1 with team Renault).

> *"The Australian Chris Dyer—that everyone pointed as the main cause of the decision in Abu Dhabi that costed Fernando Alonso the world title—had been late to come back…Last December, he was fired from his role as head strategist because of his decision on November 14, for that mistake, for that moment when Alonso entered the box too early, at lap 16, to copy Webber, and lost any opportunity to win the world title…"*
> *(Sanz, 2011)*

Today, after more than 7 years from that historical moment, and despite the many technological and organizational upgrades undergone to prevent such mistakes and improve several aspects of its their DSS, Ferrari has still not won the F1 Driver's World Championship.

Towards a more holistic interpretation of the case

While media and expert explain decision-making solely through an individual bounded cognition lens, our analysis of the case sheds light on three additional challenges beyond individual cognitive biases. The data we collected about the case, together with the practice-perspective that guided our analysis of this data, first suggest that the material and social context of the decision-making situation needs to be included in the analysis in order to derive useful lessons from this failure (see aggregate dimension 1 in Table 2). We found for instance that the ergonomics of the situation played a role: the pitwall location as a decision place can create possible causes of distractions (e.g., loud cars passing by the pit-lane and thus next to the pitwall; television broadcasting and photographers shooting the decision-making process; weather conditions such as hot temperature). Also, despite being placed right next to the starting grid, the pit-wall crew is facing a wall of flat screens that create a visual separation/distance between the decision makers and the actual race. In addition, our case suggests that the broader organizational context in which the decision is made is of crucial importance to understand decision failures. Ferrari's strong chain of command and hierarchical structure —with little possibility of bottom up interventions and unilateral responsibility attribution to the Chief Strategist—, as well as a specific organizational culture that favors blaming and 'scapegoats'—and which in recent years brought the team to substitute three acclaimed senior technical executives (Chris Dyer, Aldo Costa, and James Allison) and two sporting directors (Stefano Domenicali, and Marco Mattiacci) as a response to disappointing racing results—impacted on the decision maker. Other elements can help understand the decision failure, including the under-specialization of the professional role of the Chief Strategist at Ferrari that at the time was a part-time task for engineering directors; and a clear rule that prevented from disregarding the output of the DSS. This latter element seems crucial in our case, as reported by our interviewees. Yet, the DSS was programmed to feed-back only two options and Dyer, who was required by team procedures to pick the best option out of those offered by the DSS, correctly picked the best of the two. Unfortunately, this was not good enough to keep the 4th position and win the championship:

> *"We were deciding between A and B, and we chose A. What we miss in the end was option C, which at that time still looked a much better option. Option C was quite different from A and B. A and B were stop-now or stop in 5 laps time, option C was stopping in 15 laps time or something. (...) Option B was kind of local maximum, it was better than one lap before, better than one lap after B, better the two laps after B, but it actually it was not better than 10 laps after B. So, fundamentally, we missed option C. The option C would have put us in the position to finish fifth or perhaps fourth at the end of the race." Chris Dyer, Head of Strategy at Ferrari (interview, 2015).*

This "third option" (that had reasonably higher chances of winning) was not included among the DSS options, and following it would have meant for Dyer disregarding the team rule. This would have not been a problem, in case this option brought Ferrari and Alonso to winning the championship; but as F1 is a turbulent environment where anything can happen and results can be reverted by random happenings like a tire puncture, in case of failure (with a unique decision maker, and a blame culture) this decision would have put Chris Dyer in hard-to-justify position with his superiors. This point shows the importance of deeply understanding the organizational culture where the decision takes place, since this culture shapes decision-makers' perception of what the DSS affords them to do, and their final actions.

A second important insight that emerges from our analysis as key to understand the several causes of the decision failure is *distributed cognition* (see aggregate dimension 2 in Table 2). This notion refers to the sharing the cognitive tasks between people, and with artifacts across time. In our case, the interplay of Ferrari team members in charge of the race strategy, such as Chris Dyer (Head of Race Strategy), Andrea Stella (Fernando Alonso's Race Engineer), and Robert Smedley (Felipe Massa's Race Engineer), their mutual communication practices and their interaction with the DSS to define the pit-stop strategy also partly explains the decision that was taken. For example, it is reasonable to suggest that the location of the remote garage of analysts in Ferrari's headquarters (Maranello, Italy) far away from the race track, influenced the decision-making process. Importantly, recognizing the distributed nature of cognition leads to a closer analysis of the interactions between the human agents involved in the decision-making practice and the technology. In fact, the material aspect of distributed cognition reveals as the decision maker relied on an advanced DSS under the assumption this would compute the best possible strategy. The decision was communicated via radio to the other team members—which could reveal challenges due to noise and/or lack of visual contact; and ultimately the DSS suffered from a temporal distortion because its basic assumptions and underlying parameters could not be significantly updated during the race (for example there was no way to input a lower likelihood of successful overtaking, as it emerged during the race).

Third and finally, our case suggests that greater attention should be paid to the *performative* aspects of the DSS (see aggregate dimension 3 in Table 2). Evidence from the field revealed that complex algorithms in the simulation system and the DSS provided hard-to-manage inputs in the decision-making process. There was however hardly any possibility to integrate the emerging decision maker's intuition in the decision process or in the DSS. Further, the model did not provide probability estimates on the different options (e.g., there was no indication on their probability of leading to a positive outcome, nor what was the probability difference between these options and the other alternatives) nor it included a learning function that could have refined its outcome based on the difficult overtaking that every driver was experiencing during the race. In simple words, the system could not update some key changing conditions that emerged during the race such as the general difficulty to overtake. Information and data held a performative function as well. In general, DSS appeared to be relatively 'firm-based'—that means that the instruments tended to focus on data of the team's car (e.g., focus on Ferrari), while developing more limited insights on competitors. Further, there were no historical data on relevant parameters of the Yas Marina circuit (i.e., likelihood of overtaking in this specific circuit) as this was the first time F1 was racing in UEA.

In summary, Chris Dyer himself publicly acknowledged his mistake but nonetheless emphasized how this was the best possible solution (and the only allowed) given the two options that the DSS had suggested and given the overall constraints. A perspective mainly focused on individual cognitive bias fails to provide a more comprehensive understanding of the broader challenges in the decision. Simply put, Chris Dyer's mistake was influenced by a complex and intricate combination of factors that included not only his personal judgment, but also a miscalculation of the DSS that was embedded in a system of practices that did not allow the decision-maker to disregard it and a set of contextual features that exacerbated the situation: such as time and psychological pressure; the impossibility of directly observing the race; and mediated communication with other key agents (among others). Evidence we collected from the field by adopting an integrated practice-based perspective suggests that to reach a deeper and more systemic understanding the interpretation of the facts includes, in addition to *Individual bounded cognition,* three other key aspects *(1) Situated nature of the decision-making process / Affordance; (2) Distributed cognition;* and *(3) Performativity.*

The fact that even iconic and visible events involving performance- and technology-driven companies such as Ferrari receive a narrow and individualistic interpretation of failure and success drives home a sound and compelling case for a more holistic approach in future research on decision-making. The case from Formula 1 should support such an agenda as it represents a world that has traditionally pioneered the most advanced decision support systems (including big data) and is famous for meticulously analyzing every decision in order to optimize any outcome down to a fraction of a second—as this could separate the winners from the losers. Every detail counts. Thus, in the following section, we leverage reflections from this case to discuss implications for strategic IS and suggest a practice-based agenda.

DISCUSSION: TOWARDS A RESEARCH AGENDA

As a direct consequence from our insights into the case, we discuss and derive an agenda for research for IS scholars around three lines of inquiry: (1) The material and social features of the decision situation, including the specificities of the organizational culture that impact on decision-making (e.g., blame culture) and the interpretive flexibility (or affordances) of DSS; (2) The distributed nature of cognition along three dimensions, namely temporal (i.e. cognition is distributed across time), social (i.e. the division of cognitive labor between individuals), and material (i.e., human beings interact with non-human entities in decision-making with big data); and; (3) The performative dimension of the models incorporated in big data decision tools. Along these lines, we generalize to the field of strategic IS and advance a set of theoretical reflections that deserve attention before including the specific view of design science and tools that follows from these reflections. The agenda stems from the perspectives outlined in Table 3.

[Insert Table 3 about here]

The situated nature of decision-making

Decision-making with DSS and big data is a situated activity, that is an activity that takes place in a social, physical, and technical environment. Recognizing the situated nature of decision-making with DSS and big data allows conceiving it as social practice, and thus directs our attention to the features of the decision-making situation that might influence decision-makers' perceptions of what the technologies they use afford them to do (Gibson, 1979). This line of inquiry thus suggests studying how some elements of the organizational culture influence the way organizational actors make sense of the decision situation (e.g., blame vs. just culture, accountability) as well as the ergonomics of the decision situation such as the visual and audio environment (e.g., Schein, 1985; Suppiah & Singh Sandhu, 2011; Weick, 1987). Ultimately, it directs our attention to decision makers' perception of the interpretive and material affordance for action provided by DSS with big data decision-making technologies. Table 4 lists some of the research questions associated to a situated approach to DSS with big data decision-making practice.

[Insert Table 4 about here]

First, a practice-based approach to decision-making with DSS and big data shows the importance of considering seriously the social and material context of deciding with such technologies, and the features of the situation within which decisions are made. It could lead strategic IS scholars to explore the practices of decision-making with big data (e.g., how do organizational actors use big data DSS?) and to identify the features of the decision situation (e.g., spatial layout of the work environment) as well as the organization's decision culture that impact on decision-makers' perceptions of the affordances of DSS. The notion of "affordance" (Gibson, 1979; Hutchby, 2001) refers to the idea that the objects and artifacts that actors use are subject to "numerous interpretation and uses and [do] not allow, or 'afford', any interpretation or use: [their] constituent properties have specific effects on actions" (Giraudeau, 2008: 294). The literature on affordances in management (e.g., Giraudeau, 2008; Jarzabkowski & Kaplan, 2015; Orlikowski & Scott, 2008) shows that the intentions of the tool's designers and the material properties of the tools are not the sole determinants of the ways management tools or technologies are used. These two elements matter, but the context of use also matters since it influences how users interpret what the tools allow them to do, and therefore how they use it—that means their affordances. It is important to note that, while this approach considers that "the materiality of an object favors, shapes or invites" a set of specific uses, it also recognizes that the materiality of an object "at the same time, constrains, a set of specific uses" (Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007: 752). In-depth qualitative studies focusing on the affordances of DSS with big data could help address these questions and reveal the usage flexibility of such tools.

Second, strategic IS researchers could study the effectiveness of distinct cultures of DSS use in order understand if some cultures of use of DSS with big data lead to greater decision quality than others. Strategy researchers have long studied the relationship between decision quality and decision processes (Dean & Sharfman, 1996; Elbanna & Child, 2007; Fredrickson, 1984). Yet, this research has yielded mixed results (see Forbes, 2007 for an overview) and it is not clear whether such decision processes always pay in terms of decision quality. Strategic IS scholars could contribute to this debate by bringing in the notion of affordances. It would be important to consider how analytical decision tools (such as big data decision systems) are used in practice, and how different cultures of use of these tools are related to decision quality. Having decision tools that enable extensive data collection and comprehensive data analysis is important, but might not be enough to improve decision quality. Ultimately, what matters is the way these tools are used. In-depth qualitative studies recognizing the flexibility of use of DSS with big data could help better understand how decision systems improve decision quality: How are big data decision tools used in practice to make decisions? What organizational capabilities are needed to use big data effectively? And what cultures of uses of big data DSS best enhance decision quality and performance?

Third, strategic IS scholars could also study how the introduction of big data DSS change an organization's decision-making culture. The causal links between the cultures of DSS use and the organization design and routines are likely to be complex. Cases are needed to establish the effects of the use of DSS with big data on how members of the organization make decisions, collaborate, communicate, and jointly make use of the systems in place. Conversely, the IS assumes a strategic role and their design is likely to affect the way decision-making integrates into management functions and controls. Further, the microstructures of a DSS and the access it provides to data, scenarios, levers for action and so forth, may impact on the way decisions are taken and the ultimate performance of the decision-making process. Ditto, the role of the pitwall in F1 represents a stark example for the critical role of a DSS layout in physical space and its use in time.

The distributed nature of cognition in decision-making

Decision-making with big data involves the use of DSS if only to make the volume and speed of available information manageable for the decision makers. While one set of research questions relates to the system itself and its use in a specific cultural and organizational context, there is a second set of questions that points to how cognition—understood as a temporally, socially and materially distributed phenomenon—operates when deciding with big data DSS. We need more understanding of the cognitive roles played by big data DSS and how such systems interact with the information processing activities of their users (Norman, 1991). In his seminal work, Hutchins refers to cognitive systems that function inside individuals, between individuals and their use of tools, in a group of individuals in interaction, or between a group and their use of tools (Hutchins, 1995a: 373) and points to the possibility that cognition is distributed across time, with the notion of pre-computation. Recognizing that cognition is diffused beyond the mind of a single individual has important consequences for an analysis of decision-making with big data DSS, because the decision makers rely on support systems as well as on each other as a group.

As the F1 case shows, despite recent technological advances, the DSS are still far from being fail-safe, and their limitations are exacerbated under pressure and time constraints. In retrospect, decision makers tend to blame each other rather than understanding the implications of the distributed agents involved in the decision: for developers of strategic IS a more precise understanding of decision-making role distributions among human and non-human agents is fundamental to attribute improvements and innovate.

[Insert Table 5 about here]

In Table 5, we identify three illustrative research questions to help understand the distributed nature of cognition when strategic IS plays a key role. First, recognizing the distributed nature of decision-making with big data DSS directs our attention towards the interactions between human (e.g., the decision-makers) and non-human (e.g., big data decision tools) actors involved in the decision-making situation. This calls for fine-grained studies of the interactions between decision-makers and DSS during the decision-making process. For example, during a F1 race: Which systems and individuals are involved in which part of the analysis that leads to a decision to stop the car? Who is reflecting on the impending decision with which analysis and data?

A second set of questions that IS scholars could investigate relates to the distribution of decision-making tasks across team members and through time. They could, for instance, test the interactions between the multiple decision makers and the DSS and ultimately study the implications of pre-computation on the way decision-makers perceive what the tools' affordances are. In doing so, they could also explore regularities for consistency with interpretations and organizational routines. Third and finally, in-depth investigations of the distributed nature of decision-making with big data DSS can help understand the ways in which such tools extend human cognitive capabilities, by limiting some well-known decision biases. Recent studies in the field of cognitive psychology show that decision biases (Kahneman & Tversky, 1982; Manktelow, 2012) can be limited by an effective use of material artifacts (e.g., Vallee-Tourangeau, Abadie, & Vallee-Tourangeau, 2015; Villejoubert & Vallée-Tourangeau, 2011). We still do not know, however, the extent to which the use of artifacts, such as big data DSS, limit some of these biases (and if so, which ones?) and therefore play the role of cognitive artifacts extending human cognitive capabilities; or, if decision-making practices associated with the use of big data DSS lead to new types of decision biases. Strategic IS scholars could address these questions by using a distributed cognitive perspective that study the effects of material artifacts on decision-making.

Decision-making in practice: The performativity of models

The concept of performativity, as developed in economic sociology (Callon, 1998; MacKenzie, Muniesa, & Siu, 2007), directs our attention to the role of expert bodies of knowledge (e.g., theories, formulae, models) in the functioning of the economy and organizational life. An expert body of knowledge such as economics does not simply describe an existing external economy but actively participates in the economy and can even 'perform' (or bring into being) that economy that it is meant to describe (Callon, 2007). Building on this concept, and strategy-as-practice research, Cabantous and Gond (2011) have argued that rational decision-making is something that organizational actors make possible by mobilizing, in their daily practice, decision-making tools rooted in rational choice theory. In using these tools, they bring into being a specific theory of choice, namely rational choice theory (Cabantous & Gond, 2011; Cabantous et al., 2010).

Generally, approaching decision-making as a performative practice recognizes the social activities that produce decisions, and, importantly, directs our attention to the theories (and assumptions) embedded in the tools used to support the decision-making. This notion helps capture the ways in which a model (or a 'representation of reality') interplays with the world it describes, and reveals how the models and the contexts of application wherein they function are mutually generative and selective. As applied to decision-making with big data DSS, such an approach questions the relationship between big data DSS and the 'reality' they are supposed to describe by revealing the co-creation and the potential feedback loops between the properties of the models and the effects of action based on the models. For instance, MacKenzie and Millo (2003) show how the Black-Scholes-Merton formula for option pricing progressively acquired a performative power. A central element in their story is the incorporation of the formula into portable programmable calculators used by traders at the Chicago Board Exchange. The more traders used these devices to calculate the price of options, the more the formula became predictive of option prices. In other words, the formula, which initially did not well represent the reality of option pricing, eventually provided an accurate description of reality as traders relied on devices that incorporated the formula.

Cabantous and Gond's idea that rational decision-making, in practice, is performative can serve as a foil to a deeper exploration of the kind of performative processes and outcomes associated to the practice of deciding with big data. Table 6 summarizes the three sets of research questions associated to our enquiry into the performative nature of the practice of deciding with big data.

[Insert Table 6 about here]

A focus on the performativity of decision practices first foregrounds the analysis of the models (e.g., optimization models, multi-criteria decision models) that are encapsulated into decision tools. Such an approach to decision-making seems especially promising in the case of big data DSS, since these systems include complex 'models,' materialized into software and hardware. These systems are, like any models, intermediary devices between theory and data; they embody a simplified way of representing reality (Morgan, 2012). As a result, when decision-makers use big data DSS, they rely on these ‘models’ to act, and hence enable the model to impact on social reality. In this perspective, the relationship between users and system forms agencies of assessment capable of enacting different realities (Cecez-Kecmanovic et al., 2014b). In other words, models inside DSS are not only representations of reality but also actors (generators of actions) that impact the reality that the model is supposed to represent. Yet, we are only at the beginning of research about the models (as representations of reality and as actors themselves) encapsulated in and enacted in the use of DSS. The specific inclusions and exclusions of data create relations between the DSS and their users that perform reality and can be considered acting in multiple rounds: design, use, reuse, and so forth.

Approaching decision-making with big data DSS as performative practice also raises a question as to the type of performativity that can emerge from such tools. MacKenzie (2007) distinguished between three types of performativity. “Barnesian” performativity happens when the use of a model or formula alters decision-making processes and makes them more similar to their depiction by the decision model (as in the case of the Black-Scholes-Merton formula). This type of performativity is rare. Two other more common types of performativity are “generic” performativity—i.e., when actors use decision model in their practice —, and “effective” performativity—i.e., when the use of a decision model has an impact on decision-making processes. With which type of performativity—generic, effective, or Barnesian—are big data DSS models associated?

Third, our case showed that in some contexts, DSS using big data play a key role in strategy and that some ways of using DSS can have devastating effects. Understanding their performative potential becomes particularly critical in cases when decision makers need to act under time pressure and limited information. If big data DSS allow actors to be potentially more performant by making better decisions—partly thanks to the performativity of the system—then research is compelled to investigate the feedback loops associated with the use of big data DSS (e.g., their learning effects). How do observers and market participants understand the performativity of the DSS they use? What are the elements that drive performance and how is the impact attributed to the systems in use, the availability and analysis of big data, and the practice of systems use?

It is here that the three elements of our research agenda converge because decision makers act with and through DSS. For example, race engineers closely observe competitors’ behaviors and make decisions based on how they believe others strategize including the recursive loops implied. This affects the practice of decision-making with the DSS, the distributed cognition of the decision makers and their organizational environment, and the performativity of the support systems. Big data, as well as increasing pressure and turbulence in the environment exacerbate the underlying effects. Only a comprehensive, integrated agenda can link these seemingly separate questions. Appropriate research designs include the information technology explicitly in the analysis (Orlikowski & Iacono, 2001) and theorize within a complex web of practices, events, and results. We turn to more specific issues for strategic IS next.

CONCLUSION

Starting with a closer look at the Abu Dhabi F1 race in 2010 we ground our observations of strategic decision-making with big data DSS in an empirical analysis of the case and identify three understudied areas of research for IS scholars interested in improving decision-making practice and understand such phenomena from a systemic perspective. To have a comprehensive understanding, all three domains need to be carefully considered through an integrated perspective. First, the affordances of the DSS require attention: organizations specify systems according to their needs and build special and temporal structures that influence the decision-making practice, and ultimately contribute to the firm's strategy. Research could benefit from attending to a number of questions pertinent when taking a practice-based view on strategic decision-making. Further, decision-making is a collective task and thinking in organizations occurs collectively. A practice-based approach to decision-making with big data DSS invites IS scholars to fully recognize the distributed nature of cognition, not least because deciding with big data DSS enhances the volume and speed of information and requires interpretation via multiple decision makers. Lastly, we have argued that a practice-based approach to decision-making with big data DSS points to the overlooked performativity of DSS and invites strategic IS scholars to build on insights from recent research on model use and performativity. DSS make extensive use of models with their necessary simplifications and assumptions. Understanding the working of the assumptions in practice, the feedback loops, and the performative effects is important in identifying biases and potential failures ahead of time.

Finally, because our findings challenge the design of the tools themselves, we derive two implications of our research for research designs in strategic IS. The development of artifacts in information technology is the domain of design science (Gregor & Hevner, 2013; Hevner et al., 2004; March & Smith, 1995). As data stems from multiple sources within and beyond the organization, a first implication of our research is that the development of any DSS system needs to take into account the dynamic technical environment of a context that is being developed by multiple stakeholders. This could result in the need to design for incompleteness (Garud et al., 2008) and close consideration of the relationship between the technological artifacts and the users (DeSanctis & Poole, 1994; Markus & Silver, 2008). In particular, affordance and the potential openness of the design to other organizations and individuals in the environment (von Krogh & Haefliger, 2010) point to implications for design science. In a competitive arena such as F1, where rules and standards dictate a framework for innovation of the automotive and support technologies (Aversa et al., 2015), the focal organization is not alone and the decision maker does not act in isolation. Taking the team-level knowledge, dynamics and the competitive dynamics into account creates additional complexity for the design of the system (Erden, Von Krogh, & Nonaka, 2008).

Second, the design of IS follows feedback cycles in as far as the competent building of artifacts draws on knowledge in rigorous implementation and on problems in relevant implementation (Hevner, 2007). In this respect, design science influences and is influenced by the practice of use (DeSanctis & Poole, 1994; Markus & Silver, 2008; von Krogh & Haefliger, 2010) and new research designs should focus on how the perception, treatment, and interpretation of data systematically influence decision-making, if they do. This is part of the DSS yet more subtle than the programming itself. Following the example of F1, the sensory data from the car on the racetrack may receive a certain weight in the decision-making process relative to the communication data. This relative weight of data sources, the time delays, and other factors are programmed and modeled into the DSS and may favor specific outcomes. Such outcomes, if systematic, may in turn reinforce requirements to be programmed into the system and support the models chosen, hence an effective performativity of the DSS. A hypothesis at this point, we suggest research design in strategic IS to carefully appreciate the potential performativity in the design through the models used and the assumptions made.

Scholars have highlighted how understanding the implications of DSS and big data is (and will increasingly be) at the core of firms' performance and competitive advantage. Such technologies underpin the creation, development and performance of strategic decisions related to business models, work-practices, stakeholder interests, organizational models (Günther et al., 2017). Failing to appreciate the nuanced implications of such contemporary phenomena can lead to severe costs and organizational failure. Hence, we posit that fully understanding (in an integrated fashion) the effects of decision-making with DSS in practice, represents a paramount aspect that deserves scholarly and professional investigation.

The race to lead the "big data revolution" (Mayer-Schönberger & Cukier, 2013) keeps going within and beyond the racetrack but challenges remain compelling. Formula 1, again, exemplifies this situation. Particularly after Ferrari's fiasco in 2010, teams have significantly increased their investments in trying to optimize these critical decision-making processes. Yet, the challenge is far from being fully resolved. For example at the 2015 Monte Carlo Grand Prix Mercedes failed to transform the information of its DSS and, by making a wrong pit-stop call, jeopardized their driver's, Lewis Hamilton's, victory (Johnson, 2015). The software as well as inter-team communication were blamed for the mistake, which is particularly noteworthy given the fact that Mercedes was recently awarded for developing the best DSS visualization tool in F1 (Caskill, 2015). All in all, this confirms that even in fields that pioneer the most advanced DSS with big data, unveiling the perils and pitfalls of technology-based decision-making still represents a timely and compelling task with major strategic implications. We hope that our agenda will stimulate scholars and executives' inquiring and ultimately contribute valuable insights for theory and practice.

ACKNOWLEDGEMENTS

We gratefully acknowledge insightful conversations with colleagues Charles Baden-Fuller, Andrea Carugati, Lars Frederiksen, Gianvito Lanzolla, Elena Novelli, and Alessandro Rossi. This paper benefitted from constructive audience feedback at the Digital Transformation and Strategy Forum (Cass Business School); and presentations at the Scientific Workshop on the 4th Industrial Revolution (University of Trento), The Barclays Data Science Unit, Aarhus University, and the Israel Strategy Conference. We thank also Daoming Zhou for data collection as well as Chris Dyer, Piergiorgio Grossi, Otello Valenti, and other industry informants for their invaluable time and expertise as well as Bob Galliers for expert editorial guidance. Finally, we thank Camillo Negroni for constant support and inspiration. All authors contributed equally to this manuscript. This work was supported by the European Commission's Marie-Curie Actions [Project nr. 301688, Project Acronym AJ86RH5GYM, FP7-PEOPLE-2011-IEF]

FIGURE 1
DSS With Real-Time Big Data in Formula 1 Racing

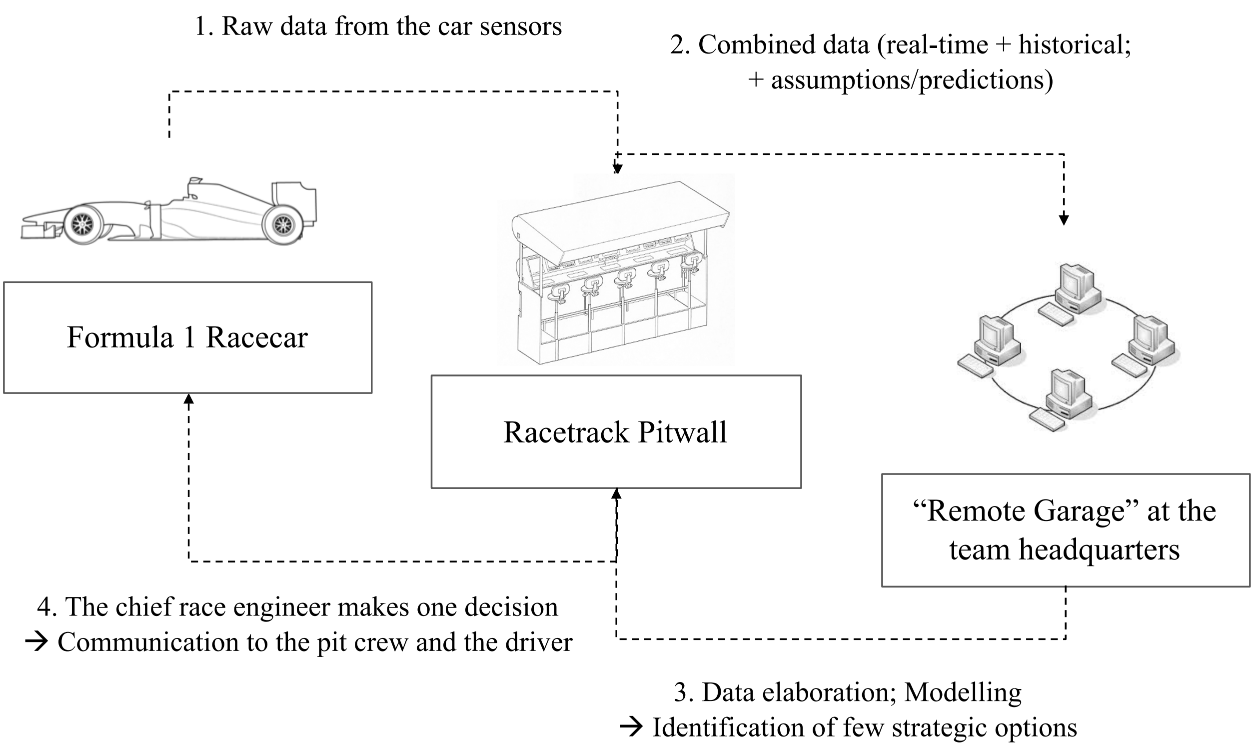

TABLE 1
2010 Abu Dhabi Grand Prix Statistics

Rank	Driver	Constructor	Laps	Time/ Retired	Start Grid	Pts	Pit-stop at lap
1	Sebastian Vettel	Red Bull-Renault	55	39:36.8	1	25	24
2	Lewis Hamilton	McLaren-Mercedes	55	10.162	2	18	23
3	Jenson Button	McLaren-Mercedes	55	11.047	4	15	39
4	Nico Rosberg	Mercedes	55	30.747	9	12	1
5	Robert Kubica	Renault	55	39.026	11	10	46
6	Vitaly Petrov	Renault	55	43.52	10	8	1
7	Fernando Alonso	Ferrari	55	43.797	3	6	15
8	Mark Webber	Red Bull-Renault	55	44.243	5	4	11
9	Jaime Alguersuari	Toro Rosso-Ferrari	55	50.201	17	2	1
10	Felipe Massa	Ferrari	55	50.868	6	1	13
11	Nick Heidfeld	BMW Sauber-Ferrari	55	51.551	14		15
12	Rubens Barrichello	Williams-Cosworth	55	57.686	7		18
13	Adrian Sutil	Force India-Mercedes	55	58.325	13		47
14	Kamui Kobayashi	BMW Sauber-Ferrari	55	59.558	12		33
15	Sebastien Buemi	Toro Rosso-Ferrari	55	+1:03.178	18		37
16	Nico Hülkenberg	Williams-Cosworth	55	+1:04.763	15		46
17	Heikki Kovalainen	Lotus-Cosworth	54	+1 Lap	20		41
18	Lucas di Grassi	Virgin-Cosworth	53	+2 Laps	22		1
19	Bruno Senna	HRT-Cosworth	53	+2 Laps	23		1
20	Christian Klien	HRT-Cosworth	53	+2 Laps	24		1
21	Jarno Trulli	Lotus-Cosworth	51	Rear wing	19		28
Retired	Timo Glock	Virgin-Cosworth	43	Gearbox	21		40
Retired	Michael Schumacher	Mercedes	0	Collision	8		-
Retired	Vitantonio Liuzzi	Force India-Mercedes	0	Collision	16		-

TABLE 2
Data Source and Data Structure

Data Source	**First-Order Concepts**	**Second-Order Themes**	**Aggregate Dimensions**
Media and external informants.	Switch of attention from achieving the actual goal (ending the race in 4th position) to out-racing the closest competitor (Mark Webber, which in the end represented a minor threat compared to Sebastian Vettel).	Cognitive biases.	0- Individual bounded cognition.
	Fernando Alonso was one of the best drivers in overtaking, held the highest number of points at the beginning of the race, and was racing with a very quick car (Ferrari).		
	Time pressure during the decision (there are only few minutes and laps to ultimately decide whether to pit or not).	Factors enhancing cognitive biases.	
	Task overload (many different technical tasks must be performed during the racing weekend).		
	Novelty of the situation (first race ever in Abu Dhabi).		
Direct observation, primary evidence and interviews with the main actors.	Possible causes of distractions in the decision place (e.g., cars passing next to the pitwall).	Ergonomics of the decision-making situation.	1-Situated nature of the decision-making process / Affordance.
	Visual separation/distance between the decision makers and the actual race.		
	Unique responsibility of the Chief strategist in the decision.	Organizational culture.	
	Organizational culture favoring blaming and ‘scapegoats.’		
	Hierarchical structure (chain of command in decision-making).		
	Under-specialization of the professional role.		
	Impossibility to "ignore/disregard" the output of the DSS.		

Data Source	First-Order Concepts	Second-Order Themes	Aggregate Dimensions
Direct observation, primary evidence and interviews with the main actors	Several people involved in the analysis of the data (but a single decision maker).	Social distribution of the cognitive task (DM).	2-Distributed cognition.
	Reliance on DSS to compute the best strategy.	Material distribution of the cognitive task (DM).	
	Radio-mediated communication (possible noise, no visual contact).		
	Impossibility to modify or adapt the DSS during the decision process.	Temporal distribution of the cognitive task (DM).	
	The parameters for the underlying assumptions in the model are set before the race.		
	Assumptions based on complex algorithms, and the DSS which provide inputs in the decision-making process.	Technical specificities of DSS and assumptions embedded in DSS.	3- Performativity.
	No possibility to include intuitive judgment in the decision process or the DSS.		
	The model does not provide probability estimates on the different options (e.g., the decision makers is only informed about which are the best options, but there is no indication on their probability of leading to a positive outcome, nor what is the probability difference between these options and the other alternatives).		
	The model does not have a learning function (it cannot include some changing conditions emerged during the race such as the general difficulty to overtake).		
	Firm-based DSS system (i.e., the instruments tend to focus on data of the team's car, while developing limited insights on competitors).	Information, data.	
	No historical data on relevant parameters (i.e., likelihood of overtaking in this specific circuit).		

TABLE 3
The Three Facets of the Phenomenon and Research Questions

Facets of the phenomenon		**Research questions**
Situated nature of decision-making with big data	Features of decision-making situation, including the elements of the organizational culture that play an important role in the way organizational actors make sense of the decision situation (e.g., blame vs. just culture, accountability), the ergonomics of the decision situation (e.g., visual and audio environment). These characteristics of the decision situation shape how actors interpret what the DSS allows them to do.	What are the characteristics of the decision situation in which actors use the DSS features and how these characteristics shape actors' perception of the DSS affordances?
Distributed cognition in big data decision-making	Fine-grained account of the collectives of human entities, and non-human entities (e.g., technologies, algorithms) making the decision. Description of the cognitive division of labor between team members (social distribution), and of the ways in which the cognitive decision task is distributed across time (pre-computation), and with the artifacts (e.g. DSS) used by actors to make the decision (material distribution).	How does the socio technical 'agencement' of the human and non-human actors lead to decisions?
Performative dimension of decision-making tools	Assumptions embedded in the Ferrari DSS have been enacted through the decision-making process. How were unexpected events modeled (e.g., safety car, competitor's change of strategy; possible accidents) and how does the responsibility of the decision maker vary? What is (not) included in the model?	How do the theories and assumptions encapsulated into DSS actively participate in decision-making?

TABLE 4
Studying the Situated Nature of Decision-making with Big Data

Research questions	**Research designs for Strategic IS**
1. How do the systems interact with the use and design of the spatial layout of the work environment when decision-making is based on big data?	Study the social decision context of DSS by exploring the micro-practices of decision-making with big data taking into account the perceptions of affordances of DSS.
2. What are the cultures of uses of big data DSS, and how do they best enhance decision quality and performance?	Compare social decision contexts of DSS, decision-making cultures with DSS (including affordances) across organizations. Compare practices and systems use over time and across space and the use of similar DSS across organizations in comparable contexts.
3. How do the uses of big data DSS change an organization's decision-making culture (e.g., effects on organizational reconfiguration; governance)	Given complex causal effects, explore cases where management designs strategy processes and governance in coordination with strategic information systems and big data use.

TABLE 5
Studying How Cognition is Distributed in Decision-Making with Big Data

Research questions	**Research designs for Strategic IS**
1. What cognitive roles do strategic information systems and decision tools play in decision-making?	Trace the interactions between decision-makers and DSS systems during the decision-making process, for example during a F1 race. Which systems and individuals are involved in which part of the analysis that leads to a decision? Who is reflecting a decision with what?
2. How is the cognitive task distributed across team members and through time?	Test the interactions between the multiple decision makers and the DSS. Study the implications of pre-computation on the affordances Explore regularities for consistency with interpretations and organizational routines.
3. How do big data decision tools extend human cognition and/or generate new decision biases?	Explore the extent to which big data decision tools improve human cognitive abilities and/or generate (new) biases in decision processes. Study how these decision tools reconfigure the decision task performed by human beings and if they change the balance between intuition and analysis,

TABLE 6
Studying the Performativity of Big Data Decision Support Systems

Research questions	**Research designs for Strategic IS**
1. What is the source and nature of the assumptions and information that enter big data DSS?	Establish a base-line for rational decision-making in terms of time, space, communication, power relations, cultural contexts etc.
2. What type of performativity can emerge from the use of big data DSS?	Compare devices and models with practice and outcome in terms of effectiveness and convergence or divergence.
3. What are the implications of using big data DSS given their potential performativity?	Investigate the learning effects and mimetic behavior among competitors’ use of big data DSS.

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