Industrial Marketing Management 88 (2020) 136–151

Contents lists available at ScienceDirect

Industrial Marketing Management

journal homepage: www.elsevier.com/locate/indmarman

Identifying, analyzing, and finding solutions to the sales lead black hole: A design science approach

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ARTICLE INFO

Keywords:
Sales lead black hole
Design science
Business-to-business
Lead allocation
Solution selling
Marketing research

ABSTRACT

In this paper, we apply a design science approach to help a business-to-business product-solution provider find solutions to the sales lead black hole. Our proposed solution emerges by leveraging insights from decision-making literature and operations management literature. The proposed design rules help marketing representatives assign leads more effectively to sales representatives, thereby fostering follow-up of marketing generated leads. In addition to our efforts to solve the sales lead black hole, we gain insights into how authentic marketing problems can be addressed through design research. By outlining a five-step procedure we illustrate how marketing scholars and practitioners jointly can address practical problems in a rigorous manner. The approach ensures that relevant research is conducted using state-of-the-art research methodologies. As such, the design science research approach is multi-method, multi-source, and multi-step in nature. Finally, by developing normative design rules we not only provide managers with prescriptive knowledge on what to do in certain problem situations, but also provide testable propositions that researchers can validate in other contexts. As such, the authors build on and extend the rich marketing research tradition.

Both practitioners (e.g., Marcus, 2002) and academics (e.g., Sabnis, Chatterjee, Grewal, & Lilien, 2013) claim that the so-called sales lead black hole is a perennial problem amongst B2B firms. Assertions are made that on average more than 70% of marketing generated leads never are followed up by sales (Michiels, 2009; Sabnis et al., 2013). Poor follow-up by sales reps can be attributed to several factors, including bad communication between marketing and sales (Smith, Gopalakrishna, & Chatterjee, 2006), delays in the lead management process (Hutchings, 1987), and unavailability of lead information (Järvinen & Taiminen, 2016). Although the sales lead black hole may represent a serious underutilization of investments in marketing activities, empirical research on marketing generated leads and their follow up by sales representatives is scarce. Table 1 summarizes studies in marketing that have examined sales representatives' follow-up of marketing generated leads.

Table 1 suggests several conclusions. First, previous studies have not validated (or explicitly reported) the existence of the sales lead black hole. Interestingly, it is unclear—besides anecdotal evidence (e.g., Michiels, 2009)—whether the sales lead black hole is a real problem, a perception problem, or a norm problem (Van Aken & Berends, 2018). Only when a problem is a real problem managerial action is deemed necessary. A perception problem occurs in the situation when a manager has an inaccurate opinion of the lead management process and its performance. For instance, a marketing manager may think the majority of missed sales opportunities are caused by sales reps not allocating enough time to the follow up of marketing generated leads (Sabnis et al., 2013), where, in reality, deals are not closed due to misalignment between product attributes and customer needs (e.g., wrong targeting and/or poor product design). A target problem refers to the situation when a manager has unrealistic targets. For example, in a particular company sales reps' follow-up of marketing generated leads may be around 80%—in line with comparable companies in the industry—while the sales manager demands a minimum level of 95% (which may be unfeasible because of constraints in resources). To assess the type of field problem it is crucial to take into account both norms and evidence. Failing to do so leads to academic research that is irrelevant, but more importantly, also may provide practitioners with incorrect recommendations and guidelines.

Second, previous empirical studies adopted dependent variables that do not directly capture sales reps' lead follow-up of marketing generated leads (e.g., 'lead to appointment', 'lead to booking'). Similarly, the few studies that examine the lead management process do

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https://doi.org/10.1016/j.indmarman.2020.05.008
Received 12 May 2019; Received in revised form 4 May 2020; Accepted 5 May 2020

Table 1
Relevant empirical research on sales rep's follow-up of marketing leads.

Study	Smith et al. (2006)	Monat (2011)	Sabnis et al. (2013)	D'Haen and Van den Poel (2013)	Järvinen and Taiminen (2016)	Current study
Validation of problem class: Sales lead black hole validated in sample?	No (83.7% followed up)	No (17.9% of leads converted into booking)	No (5.7% of time spent on marketing generated leads; 15.6% on self-generated leads)	No	No	Yes (< 15% followed up)
Problem framing: Consideration of lead assignment process?						
Speed	No	No	No	No	No	Yes
Quality	No	No	No	No	No	Yes
Conversion	Lead to appointment	Lead to booking	% of total time spent on marketing leads	–	–	Conversion (Lead to opportunity)
Exploratory diagnostics	Descriptive analytics, personal discussions sponsor company.	Scoring model/ discriminant analysis	–	–	Interviews	Interviews, process mining, descriptive analytics.
Explanatory diagnostics	Seemingly unrelated regression (SUR)	–	Dirichlet component regression model	–	–	Linear regression models with cluster-robust estimation
Sample	B2C	B2B	B2B	–	B2B	B2B
Data source	Archival (19,496 inquiries)	Archival (324 inquiries)	Survey (461 reps)	–		Archival (757 inquiries)
Accounts for endogeneity	Yes	Not relevant	No	Not relevant	Not relevant	Yes
Research output (artefact)	Decision-support tool (Instantiation)	Constructs	Conceptual framework (Predictive model)	Sales force automation tool (Mathematical model)	Conceptual framework	Design rules (Principles)
Validation of prescriptive model	Simulation (Alpha testing)	–	–	–	–	Expert interviews, focus groups (Alpha testing)

not take into account process related outcomes (i.e., speed, quality), which thereby may lead to erroneous interpretations. Although, Smith et al. (2006) do capture time-related effects, their business-to-consumer context leaves less autonomy for sales reps to decide whether or not to follow up, i.e., customer visits are scheduled by marketing based on capacity. This contrasts the business-to-business context described by Sabnis et al. (2013) where sales reps can choose their own leads. Yet, also the latter study does not disclose whether the examined sales reps spent less time on marketing generated leads due to speed and quality related factors. For instance, it may be possible that sales reps spent less time because it takes on average less time to process marketing generated leads compared to self-generated leads (i.e., there was balance in amount of leads processed, but not in terms of time to process both types of leads).

Third, studies generally focus either on explaining the sales lead black hole via concepts and conceptual models (Sabnis et al., 2013) or try to provide a mathematical model to aid the sales reps' decision making process (D'Haen & Van den Poel, 2013). Some studies go beyond these scientific outputs and also create tools in the form of a contextualized solution (Smith et al., 2006), also referred to as an 'instantiation' (Romme, 2016). Yet, the proposed concepts and models generally suffer from a lack of pragmatic validity as it remains unclear whether these artefacts will function in a specific setting, while instantiations suffer from external validity as it remains unclear whether the proposed solutions would function in other settings. As a solution to this, the current research introduces the concept of design rules in marketing research, which form a bridge between pragmatic validity and external validity.

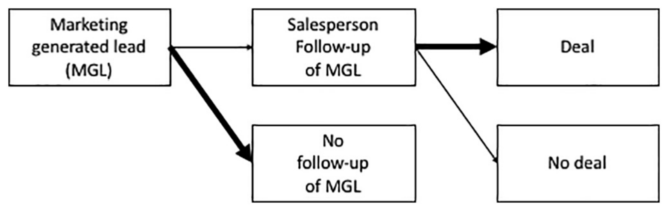
Against this backdrop, the aim of this study is to provide a structured and systematic analysis of the sales lead black hole phenomenon. More specifically, we employ a design science approach which aims to develop normative rules (i.e., design rules) to help managers make more informed decisions in their daily job. As such, we go beyond extant practice in marketing research by providing a structured approach for marketing scholars on how to analyze field problems *and* develop normative guidelines for practitioners.

Next, we introduce design science research to the marketing discipline. After that we proceed with exploratory diagnostics in which the lead follow-up literature is discussed, the managerial context is introduced, and the problem is identified. We follow with explanatory diagnostics to better understand underlying mechanisms. Based on these preceding steps we develop design rules using the CIMO-logic. Finally, we conclude with a discussion on the validation of the design rules and theoretical and managerial implications.

1. Design science research

We draw on design science research to develop a grounded model of the lead assignment process (i.e., how does it work?) and provide prescriptive knowledge for managers (i.e., 'How should it be?') (Hevner, March, Park, & Ram, 2004; Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007). The notion of design science arises from Simon's (1969) seminal work, and is the standard approach in engineering disciplines such as mechanical engineering, software engineering, and information systems, but is also widely used in disciplines such as medicine and law. Although recently some marketing scholars have utilized a design science approach (Beloglazov, Banerjee, Hartman, & Buyya, 2015; Lee, Lee, Lee, & Lim, 2013; Teixeira et al., 2017), in general—and perhaps surprisingly—marketing research has not explicitly embraced design science research to address practitioner problems. Design science relies on pragmatism, using any method, technique, and procedure associated with qualitative and quantitative research to improve "the human condition by developing knowledge to solve field problems, i.e. problematic situations in reality" (Denyer, Tranfield, & Van Aken, 2008, p. 394). While marketers may generate idiosyncratic solutions that solve local problems, design science creates

Table 2
Illustration of design based science research process.

	Research process step	Illustration	Main results	Remaining research questions
1.	Identification of focal field problem	*Problem class:* 'Sales lead black hole' 	–	■ How real is the problem? ■ What are causes and consequences? ■ How to solve the problem?
2.	Exploratory diagnostics	*Validate field problem & explore causes and consequences* (Van Aken & Berends, 2018) ■ *Establish* and *frame* problem in real-life case (problem framing). ■ Systematic literature review on phenomenon (research-based insights). ■ Conduct exploratory study in real-life case using e.g., interviews, exploratory data analysis (practice-based insights).	■ Few empirical studies. ■ Sponsor company suffers from sales lead black hole (< 15% follow-up). ■ Lead assignment is major bottleneck in real-life case.	■ What are underlying mechanisms of lead assignment process? ■ How much impact does it have on follow-up?
3.	Explanatory diagnostics	*Explanatory analysis of identified bottleneck* (e.g., MacInnis, 2011) ■ Identification of relevant theories and literature streams (Operations management; process research). ■ Appropriate conceptualization of lead assignment process ■ Development and testing of hypotheses/propositions.	Validation of conceptual model ■ Lead assignment process can be captured in terms of speed and quality. ■ Information processing theory to explain mechanisms.	■ What can managers do to change the status quo? Improve the lead assignment process?
4.	Develop artefact	*Apply CIMO-technique* (Denyer et al., 2008) ■ Identify CIMO rules from systematic literature review. ■ Create CIMO rules from empirical analysis.	Overview of managerial interventions and when useful.	■ How reliable and valid are the design rules in practice?
5.	Validate artefact	*Pragmatic validity of design rules* (Van Aken et al., 2016) ■ Expert interviews (i.e., alpha testing) ■ Formulating steps for further validation of artefact (beta-testing) and indicating boundary conditions.	■ Theoretical implications ■ Practical implications	■ Study limitations ■ Future research opportunities

novel artefacts that advance the marketing research field through an iterative process of conceptualization, creation, and validation. In general, design science research starts with the identification, diagnosis, and framing of a field problem, after which a 'solution' or 'artefact' is designed and implemented. These artefacts include generally accepted inputs and outputs of social sciences like values, constructs, and models to describe practitioner problems or challenges, but also incorporate 'design rules' and 'instantiations' that aim to solve the problems within a particular problem class.

Table 2 provides an overview of the design science research process used in this paper. First, the focal field problem is identified. The field problem belongs to a class of problems, which refers to 'the organization of a set of problems, either practical or theoretical, that contain useful artifacts for action in organizations' (Dresch, Lacerda, & Antunes, 2015, p. 104). Linking an idiosyncratic problem to a class of problems allows the identification of commonalities and differences across unique cases or field problems (for instance via systematic literature reviews and meta-analyses), thereby enabling the generalization of knowledge in that area. In the current paper, the sales lead black hole is considered such a class of problems centering around the observation that salespeople do not tend to follow up on marketing generated leads.

Secondly, exploratory diagnostics are conducted to validate the field problem and explore causes and consequences (Van Aken & Berends, 2018). There should be clear evidence that the problem is real, and not a perception or a norm problem. In addition, the problem needs to be framed. Framing can be done using different (theoretical) lenses, and often depends on the researchers involved (Holmström, Ketokivi, & Hameri, 2009). Different frames lead to different solutions, but the consideration of multiple frames may foster creative thinking. In addition, a systematic literature review provides an overview of the current body of knowledge; outlining known causes and consequences, available empirical solutions, and theories to frame the problem (i.e., gathering research-based insights). Inductive research methods such as interviews and process mining are used to examine the case at hand (i.e., gathering practice-based insights).

Thirdly, explanatory diagnostics are conducted to examine underlying mechanisms, linking causes and outcomes. Following a hypothetico-deductive approach (e.g., Dresch et al., 2015) a conceptual model is designed after which hypotheses are formulated, that subsequently are put to the test using data.

Fourthly, using the output from the exploratory and explanatory diagnostics, one or more artefacts are created to address the field problem. Ideally, these artefacts are (based on) design rules, which follow a means-end logic that links, for example, managerial actions to specific outcome patterns (Romme, 2003). Design rules are able to address a class of problems and can be seen as a linking pin between more abstract concepts, models, and theories and context specific instantiations. Instantiations (also known as empirical phenomena) are realizations of artefacts in a specific organizational context (e.g., a customer relationship management system installed at a client) that are designed using prevailing values, concepts, models, and design rules (Romme, 2016).

The fifth step involves the justification of a solution (i.e., design rule or instantiation). Design science is particularly interested in validation is terms of pragmatic validity; does the artefact produce desired outcomes? (Van Aken, Chandrasekaran, & Halman, 2016). By borrowing concepts from software development, the justification process can first go through a stage of alpha testing (i.e., verifying the effectiveness of a design rule by the researcher in the original setting) and subsequently through beta testing (i.e., where other researchers try to replicate the effectiveness of the rule in a new setting) (Van Aken, 2004).

As mentioned, different framing of the problem under investigation may lead to different solution outcomes. As such, design science scholars acknowledge that there are not universal solutions for problems, but instead argue that multiple solution artefacts can co-exist in a class of problems. Similar observations are made in engineering, medicine, and law.

2. Exploratory diagnostics

2.1. Literature review: lead process management and the sales lead black hole

The sales lead black hole refers to a class of problems associated with the sales process. The sales process or sales funnel covers the acquisition and retention of customers and consists of different stages—i.e., where potential customers are first identified (suspects), then prioritized (prospects), and finally followed up by sales (leads) with the aim to turn them into customers (D'Haen & Van den Poel, 2013). Generally, marketing is responsible for creating leads (Monat, 2011). Marketing identifies prospects out of the pool of suspects and forwards qualified leads to sales representatives who are expected to follow-up on this lead, i.e. contact the customers to analyze their needs (Selden, 1997). For example, after a marketing campaign, identified prospects may contact the company (e.g., via telephone, e-mail, or web form). When these inquiries are qualified as lead by marketing, marketing assigns the lead to a sales rep who then is expected to follow-up, for instance by calling back the prospect.

Ideally sales representatives should follow-up on each and every marketing generated lead. However, recent anecdotal evidence indicates that on average 70% of the marketing generated business-to-business leads are not followed-up by salespeople, i.e., they disappear in the proverbial sales lead black hole (Sabnis et al., 2013). Research points out several reasons for poor lead follow-up of marketing-generated leads. First, a plethora of studies indicate that the marketing-sales divide (e.g., Homburg & Jensen, 2007) leads to several issues in the lead management process, including miscommunications or distrust between marketing and sales (D'Haen, Van den Poel, Thorleuchter, & Benoit, 2016). Second, incoming leads often do not get adequate attention, causing delays in lead assignment, which lowers the chance of follow-up as the lead value depreciates over time (Hutchings, 1987; Smith et al., 2006). Third, inquiries and leads often come with limited information, making it difficult for marketing and salespeople to assess potential value and to make informed decisions (Donath, Dixon, Obermayer, & Crocker, 1994), thereby resulting in inertia (Järvinen & Taiminen, 2016). Not surprisingly, some studies attempt to develop limited information models that predict which leads are most likely to turn into deals (D'Haen & Van den Poel, 2013; Monat, 2011).

In summary, although the literature conceptualized the lead management process and offers some insights into possible reasons for the sales lead black hole, it provides limited empirical and theoretical insights into the lead assignment process itself (also see Table 1). Specifically, there is little help for sales and marketing managers on how to organize the lead assignment process and understanding how to make the best choice under conditions of limited information. We build on these gaps by exploring how the different characteristics of the lead assignment process influence actual lead follow-up. As such we take a process perspective and take into account factors related to the availability of lead information, lead processing time, the correctness of lead assignment, and eventual follow-up.

2.2. The field problem context

To validate the field problem and explore causes and consequences we conducted an in-depth field study. Our field study is conducted in a large international solutions provider operating in the business-to-business domain, which we refer to as SOL for confidentiality reasons. SOL is headquartered in Europe and provides product-service solutions to its business customers via a direct sales process. Customer inquiries may result from marketing campaigns, but current clients and potential clients also may contact the customer contact service via telephone, web form, or e-mail. The customer contact center rep then classifies the inquiry (i.e., commercial, support request, consumer, or complaint) to determine suspects (i.e., commercial) after which the BANT-criteria (i.e., budget, authority, need, timing) are used to determine prospects. Marketing receives qualified leads together with follow-up comments (textual information) from the customer contact center rep and assigns valuable leads to individual sales reps and rejects those leads who are not of interest. The sales rep is expected to follow-up on assigned leads by (1) converting leads into opportunities (short-term), (2) assigning leads to an existing customer account (long-term), or (3) rejecting leads. In all three cases the lead is closed. Only when a lead is converted into an opportunity the lead is formally followed-up by the sales rep with the aim to close a deal.

2.2.1. Problem validation

Management at SOL asked us to examine possibilities for improving the sales funnel and the lead management process in particular. On a global level, less than 2% of marketing generated leads are followed up by sales reps. Our field study focuses on one major European market segment where on average less than 15% of marketing generated leads are followed up by sales reps. Although exact norms within the industry are unknown, the identified follow-up percentages are well below the figures reported in other studies and also deemed to be too low by the responsible managers within SOL.

2.2.2. Exploratory interviews: data collection and analysis

To get acquainted with the company context, its lead management process, and related bottlenecks orientating interviews were conducted. We identified key informants across different organizational levels and from different functional backgrounds (e.g., customer care management, digital marketing management, lead marketing automation & lead manager, sales reps, marketing reps, business information manager). Three criteria were used to select respondents: the respondent (1) was involved in the lead management process, (2) had a complete overview of all the technical and commercial aspects of the lead management process, and (3) had more than 1 year of experience within the current work environment.

We employed semi-structured exploratory interviews. General questions used in the interview were: “Where do you think the bottleneck is in the process?”, “What solution do you see for the problem”. We interviewed respondents until we reached saturation, which occurs when no new categories or properties emerge from the gathering of data. Given our exploratory approach, and relatively straightforward inquiry, we reached saturation after ten interviews.

All interviews were conducted face-to-face and took 45 min on average. During interviews extensive notes were made and summarized within 24 h. After discussions with our sponsor we decided not to audiotape interviews to ensure a low threshold for sharing (sensitive) information. Data was analyzed using open, axial, and selective coding (Glaser, Strauss, & Strutzel, 1968) to come to a core description of the problem context, its causes, and consequences. We visualized the outcome of this analysis in a cause-and-effect diagram which was validated with involved stakeholders.

2.2.3. Exploratory interviews: findings

The interviews revealed several important causes for non-follow-up of marketing generated leads which all helped to frame the problem. First, respondents indicated that many leads are ‘*assigned to the wrong sales reps’*. These leads either disappear in the lead black hole or are sent back to marketing. Second, respondents indicated that problems occur due to ‘*delays in the lead management process’*. Third, some respondents indicated that the poor follow-up is caused by the ‘*lack of information that comes along with a lead*’. This results in poorly justified decision-making and trial-and-error behavior when assigning leads. Finally, some respondents indicated that problems occur due to ‘*low capacity within the sales force’*.

A direct consequence of these issues within the lead management process is ‘*poor follow-up’* of marketing generated leads by salespeople, which results in ‘*dissatisfied clients*’ and ‘*low return of investment for marketing activities*.’

2.2.4. Process mining: data collection and analysis

To validate our exploratory interviews and explore other bottlenecks in the lead management process we conducted process mining on available company data (Van der Aalst, 2016). Process mining allows the analysis of behavior based on event data; ‘to discover processes, check compliance, analyze bottlenecks, compare process variants, and suggest improvements’ (Van der Aalst, 2016, p. 3). In specific, we used process mining to examine (1) the frequency of leads ‘*assigned to the wrong sales reps’*, (2) the frequency of ‘*delays in the lead management process’*, and (3) other bottlenecks.

Lead history data was analyzed by extracting data from the data warehouse. The data concern the lead generation and sales processes in a major European market. Specifically, inquiries in 2017 and 2018 pertain the sample; there where a total of 1377 leads (including open and closed leads), 188 followed-up leads (i.e., opportunities), and 19 bookings. At the lead level, the data set includes information about lead identifiers, events, and timestamps, which allows the usage of process mining techniques (Van der Aalst, 2016). After preparation of the data (e.g., removing test leads, adding ‘create’ and ‘closed’ states, removing open leads) we analyzed the data (873 leads, 22 event types, 10,400 events) with a commercial process mining package called Disco (Rozinat, Günther, & Niks, 2017).

2.2.5. Process mining: findings

The results provide evidence that leads are ‘*assigned to the wrong sales reps’* relatively often. Appointing a lead to the correct sales rep (‘lead owner’) often needs more than one attempt (to assign 873 leads, 1291 attempts are needed). Although 420 leads are assigned in one attempt, around 200 leads need two attempts, while more than 250 leads need three or more attempts. When examining the ‘*delays in the lead management process’* the results show that the incorrect assignment of a lead to a sales rep (i.e., > one attempt) already delays the correct assignment of a lead by 9.3 days on average, which is way beyond the company norm (i.e., 3 days). However, the data shows large variations in the processing time, thereby suggesting that the ‘*number of attempts’* and ‘*time to correctly assign a lead’* act orthogonally. In sum, the process mining analysis corroborates the main findings from the interviews. However, an empirical question remains why these bottlenecks occur and whether it affects actual follow-up by sales reps. This part will be covered in the next section.

3. Explanatory diagnostics

3.1. Theoretical background

Based on the exploratory diagnostics the problem was validated and framed as an allocation problem (e.g., McClure & Wells, 1987; McIntyre & Ryans, 1983), where in our case leads need to be allocated to sales reps under conditions of limited information and limited resources (both in terms of decision-making time and available sales reps). Specifically, we are interested to understand how availability of information affects a sales rep's lead follow-up decision as a result of the lead assignment process in terms of speed (i.e., time to correctly assign a lead) and quality (i.e., # attempts to assign a lead).

In doing so, we draw on operations management and decision-making under uncertainty literature. First, within the discipline of operations management, the Theory of Swift, Even Flows postulates that in order to increase productivity it is important to (i) lower throughput time of units (i.e., leads) by removing bottlenecks or other impediments and (ii) narrow the variability within operation steps, for instance by minimizing rework (Schmenner & Swink, 1998). This theory seems to nicely fit our context and research question. The exploratory analysis revealed that throughput time in terms of assigning a lead is a major bottleneck (i.e., '*time to correctly assign a lead*') and that there is a lot of variation in correctly assigning leads to sales reps (i.e., '*number of attempts*' needed to correctly assign the lead). According to the Theory of Swift, Even Flows, lead follow-up will be higher if throughput time is minimized and attempts to assign a lead are kept at a low, steady number. Following previous studies, we label these concepts in the remainder as 'speed' and 'quality', respectively (e.g., Dean Jr & Sharfman, 1996; Keller & Staelin, 1987; Rodriguez & Honeycutt Jr, 2011).

As the Theory of Swift, Even Flows does not make any claims on *how* people make decisions, we draw on decision-making theory (e.g., Hall, Ahearne, & Sujan, 2015; Simon, 1979; Vroom & Jago, 1974) to understand how time, information, and environmental constraints affect lead assignment. Decision-making theory posits that human decision-making is based on two cognitive processes each associated with different levels of speed and quality: System 1 (intuitive) and System 2 (deliberative) cognitive processes (Frederick, 2005; Hall et al., 2015). System 1 processes consider the more spontaneous and intuitive decision making and does not need much effort, whereas System 2 processes consider more mental activity and concentration (Frederick, 2005; Moritz, Siemsen, & Kremer, 2014). While deliberative processing of information takes more time, effort, and logic (Hall et al., 2015; Kahneman, 2003) it is believed that intuition leads to faster and better decision quality (Kaufmann, Meschnig, & Reimann, 2014).

Although high '*availability of information*' is required to make quality decisions (Aina, Hu, & Noofal, 2016), in the early stages of the sales process employees often have to work with a limited amount of information or 'thin slices'. Several streams within decision-making literature, including consumer decision-making theory (e.g., Malhotra, Jain, & Lagakos, 1982), information processing (e.g., Zhang, Phang, Wu, & Luo, 2017), and thin-slicing theory (e.g., Thompson, Hamilton, & Rust, 2005), demonstrate that information load—referring to the amount of information and the type of information people have at hand when making decisions (Jacoby, 1977)—influences the ability of people to make the right decision (Malhotra, 1982; Malhotra et al., 1982). Extant research predominantly examined the negative outcomes of information overload due to increased information complexity (Denize & Young, 2007; Hwang & Lin, 1999; Malhotra, 1982), yet some scholars points to the negative effects of information underload too, due to lower availability of cues to understand the context (Malhotra, 1982; O'Reilly III, 1980).

3.2. Conceptual framework and definitions

Our conceptual model is depicted in Fig. 1 and centers on the role of *information load* in predicting *lead assignment speed* and *lead assignment quality*, and its final effect on a sales rep's *lead follow-up*. Assigning leads correctly to sales reps depends on the amount of available lead information which is gathered in the front-end of the sales process. In this study we focus on the number of words provided by the customer contact representative (i.e., follow-up comments). We propose that under situations of high workload, employees generally adopt an intuitive decision-making approach and look for other people's input to quickly make decisions. Yet, how available information is processed depends on certain contingencies that may trigger deliberative (normative) processing of information, which takes more (less) time and effort (e.g., Hall et al., 2015). In particular, we posit that *lead uncertainty*, that is the uncertainty of converting the lead into a deal (i.e., indicated by pre-qualification level) and *customer familiarity* (i.e., existing or new customer account) influences whether the deliberate processing mechanisms are triggered or not. Finally, the performance of the lead assignment process is expected to influence the outcome of a lead (i.e., lead follow-up).

3.3. Hypotheses development

We posit that under situations of high workload, marketing representatives generally adopt an intuitive decision-making approach when assigning leads and quickly scan the input from the customer contact center to make fast decisions. Although this goes against conventional wisdom of marketing science efforts to collect massive amounts of data and invest in e-CRM, inbound systems, and other data warehouse systems,[1] research convincingly shows that higher data availability does not equal better decision making. Actually, evidence shows that higher data availability can instigate choice paralysis and lead people to become less decisive (e.g., Thompson et al., 2005). Because people are limited information processors (Newell & Simon, 1972), too much information, despite its utility, likely will introduce an information overload problem (Eppler & Mengis, 2004), especially when working under time constraints. The bounded rationality due to cognitive limitations and time, information, and environmental constraints, foster heuristic based and intuitive decision making (Banin et al., 2016). This intuitive approach is similar to the concept of "thin-slicing", popularized by Gladwell (2005), whereby accurate decisions are made in an automated and faster manner, replacing a painstaking process of analysis (Albrechtsen, Meissner, & Susa, 2009; Ambady & Rosenthal, 1992). In our case, the available textual information represents a thin slice, where judgments are based upon incomplete information.

Within our case company, interviewed employees indicated that they experienced high workloads and that lead allocation was often done during evening hours. In general, the extent to which leads carry more textual information relates to customers having more clearly defined needs or because customer contact center reps ask more follow-up questions. Since the marketing representatives work under time constraints, we posit that the intuitive decision-making approach becomes more inaccurate with increasing information load. Constraints in time generally makes people more selective in their processing of textual information as they tend to look for 'approximate' answers to a reasoning problem or question (i.e., confirmation heuristic or positive hypothesis testing) to save time and energy (Laughlin, Bonner, & Altermatt, 1999). Alternatively, thin slicing research suggests that more data availability leads to more processing of the thin slice before people make their final judgment, which impairs the decision maker's ability to interpret more implicit information that provides valid cues on how to proceed (Ambady & Gray, 2002). Overall, literature on information processing and decision making shows that decision effectiveness decreases when information load increases (Hwang & Lin, 1999; Keller & Staelin, 1987; Lurie & Mason, 2007).[2]

Likewise, the amount of available textual information is expected to have a negative effect on lead assigning speed. Studies in related fields confirm a negative relationship between available information and speed (Clark & Collins, 2002; Kahneman, 2003; Keller & Staelin, 1987). Textual information needs more time to process (Hendrick, Mills, & Kiesler, 1968; Jacoby, Speller, & Berning, 1974; Speier, Valacich, & Vessey, 1999) because of higher cognitive demands (Lurie & Mason, 2007; Speier & Morris, 2003; Trendel, Mazodier, & Vohs, 2018; Wedel & Pieters, 2000). Although one would expect that more textual information associates with more controlled, deliberative processing of information, we posit that in our research context the intuitive

[1] We thank an anonymous reviewer for pointing out this counterintuitive line of reasoning.

[2] Some evidence points out that information load has an inverted U-shaped relationship with the decision quality (Argouslidis et al., 2014; Hahn, Lawson, & Lee, 1992; Hwang & Lin, 1999), supporting claims that both information underload or information overload result in poorer decision making (Malhotra, 1982). However, in our research context limited textual information often is the result of relatively simple and clear customer requests making it easier to assess the incoming lead.

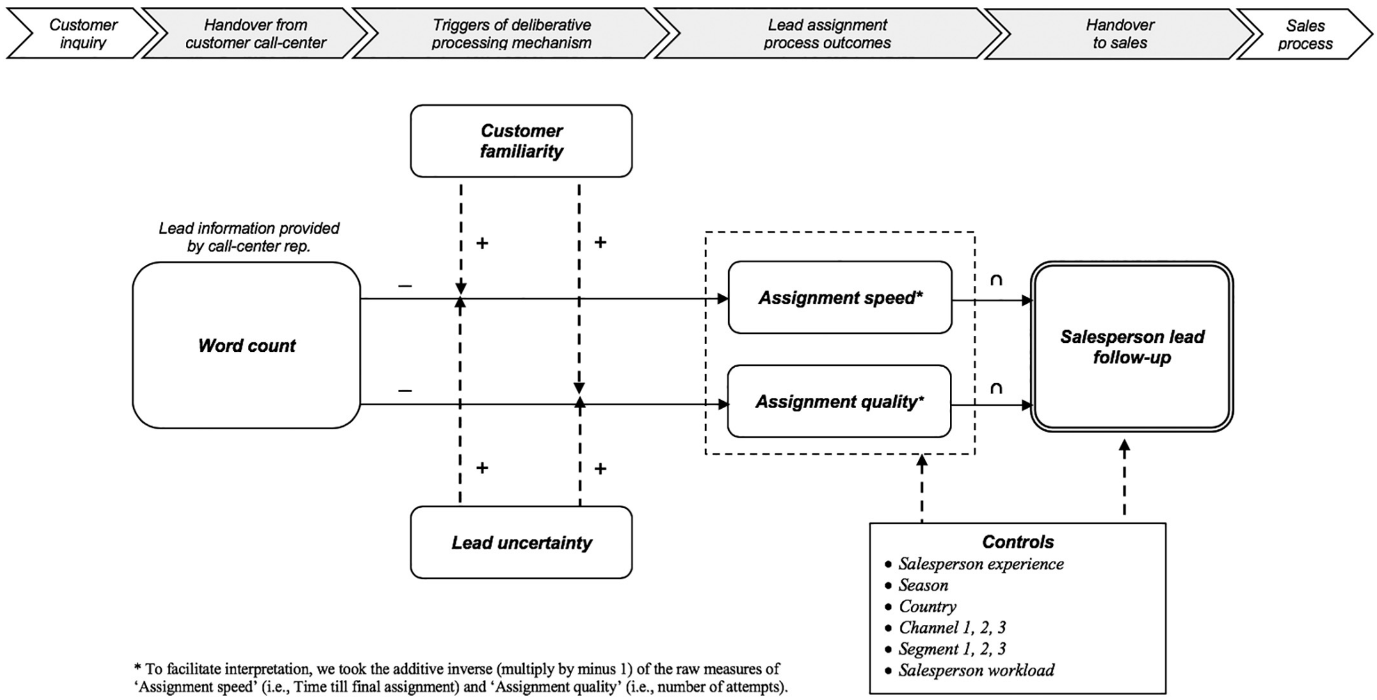


Fig. 1. Conceptual model of lead assignment process.

approach to process information remains dominant due to high workload (Banin et al., 2016). As such, time delays are likely to occur because marketing reps may prefer easier to handle leads over these more information laden leads. That is, they get lower priority. In sum, we posit that the higher the information load, the lower the quality and speed will be in the lead assignment process. Or, more formally:

H1. Information load will have a negative effect on (a) lead assignment quality and (b) lead assignment speed.

Although we posit that lead assignment predominantly occurs in an intuitive manner, decision making theories (e.g., information processing theory, thin slicing research) demonstrate that under certain conditions the decision maker, i.e., the marketing representative responsible for assigning leads, will adopt a more conscious and deliberate approach (Frederick, 2005). The change in decision-making approaches relates to the extent to which the decision maker is aware of (i.e., salience), willing (i.e., motivation), and able (i.e., capable) to consider important environmental cues (e.g., Ambady & Gray, 2002; Payne & Bettman, 2004). In frontline settings, information about the customer and the probability to make a deal are considered very salient and important cues. In particular, we examine the role of lead uncertainty (i.e., pre-qualification level) and customer familiarity (i.e., existing versus new account), which we will elaborate on next.

An important trigger for using deliberative processing is familiarity with the subject of interest (Stieger & Reips, 2016). When a lead comes from an existing customer, marketing employees tend to pay relatively more attention to his or her request. The underlying reason for paying more attention is that employees feel more committed and connected to existing relations and feel more obliged to serve them in a responsive manner (Meyer, Becker, & Vandenberghe, 2004). As such, under this condition a deliberative cognitive process is activated in which the marketing rep tends to pay more attention to available textual information. The more information will be available a priori, the easier the employee can make a quick and accurate decision. When this information is lacking, either more time is taken to collect additional information, or the lead gets a lower priority in the lead assignment process. Following from this, we posit that familiarity will trigger a more deliberative decision-making process in which a priori available information enables employees to assign leads to sales reps more quickly with fewer attempts, that is with higher quality. Or, more formally:

H2a. The negative relationship between information load and the lead assignment quality is expected to become weaker when customer familiarity is high.

H2b. The negative relationship between information load and the lead assignment speed is expected to become weaker when customer familiarity is high.

Another important trigger for adopting deliberative processing is the uncertainty that a lead will convert into a deal. Marketing and salespeople can infer the level of uncertainty from the pre-qualification level of a lead, where a lead is qualified by the customer contact center rep as "cold", "warm", or "hot". The higher the uncertainty (e.g., cold or non-qualified), the more effective it would be to make deliberate decisions (Read, Dew, Sarasvathy, Song, & Wiltbank, 2009). Research on choice uncertainty, indicates that when people face a situation where the choice of the best option is creating equivocal conflict, people are motivated to resolve that conflict by looking for relevant information (Urbany, Dickson, & Wilkie, 1989). Following this, we posit that when a marketing employee needs to assign an incoming lead with high uncertainty to a salesperson, the employee is motivated to find the best option and as such is more likely to deliberatively process available information. Under this condition, the marketing employee is better able to utilize higher availability of textual information that travels along with the lead, hence improving decision-making speed and quality. Therefore, the next hypotheses are stated:

H3a. The negative relationship between information load and the lead assignment quality is expected to become weaker when lead uncertainty is high.

H3b. The negative relationship between information load and the lead assignment speed is expected to become weaker when lead uncertainty is high.

The lead assignment quality is expected to have an inverted U-shape relationship with the probability for lead follow-up. To begin with, when a lead is assigned within a few attempts the probability of lead follow-up will be higher than if many attempts are needed. Although one may claim that this effect can be attributed to the deteriorating value of a lead over time, we posit that this effect is time independent (i.e., we control for time). The more often an employee tries to assign a lead to a salesperson, and the more often this person fails to correctly assign the lead (i.e., low assignment quality), the higher the probability is that lead will not be followed-up. We have two reasons for this. First, the receiving party may consider the employee responsible for assigning the lead incapable of assigning this lead correctly and as such devaluates the lead that is assigned to him or her. Secondly, the receiving party may get the impression that the lead itself is a “bad” lead and as such devaluates the lead. Support for this comes from theories on attribution theory (e.g., Weiner, 1974) and self-efficacy theory (Bandura, 1977).

Furthermore, due to the limited information available in the early stages of the sales funnel and the limited capacity of the sales force, it can be expected that the average lead is assigned several times before it is followed up, that is before a good match has been found. However, in our context it also can be expected that some leads that are assigned to salespersons do not get sufficient attention and are never reallocated nor followed-up by the salesperson. These leads are destined to ‘die in the pipeline’. Hence, we posit the following non-linear relationship:

H4a. Lead assignment quality will have an inverted U-shape relationship with lead follow-up.

The lead assignment speed is expected to have an inverted U-shape relationship with the probability for lead follow-up. This statement is supported by literature on decision making theories and operations management (Argouslidis, Baltas, & Mavrommatis, 2014; Robert Baum & Wally, 2003; Wally & Baum, 1994). It is known that if strategic decisions are made quickly, the probability of higher sales growth increases (Judge & Miller, 1991). Similarly, if people take more time to take a decision, this leads to a less efficient process and delays, and therefore decreases the possibility of higher performance (Jacoby et al., 1974). Yet, some studies suggest an inverted U-shape relationship between decision speed and actual performance (Argouslidis et al., 2014), indicating that being too quick or too slow both has detrimental effects on performance. On the one hand, research on lead follow-up indicates the unwillingness of salespeople to follow-up on delayed leads as their value depreciates over time (Hutchings, 1987). On the other hand, assigning leads to sales representatives too quickly may associate with lower levels of trust and quality of the assignment decision, as salespeople may understand that the assignment itself was not performed in a conscious manner. Hence:

H4b. Lead assignment speed will have an inverted U-shape relationship with lead follow-up.

3.4. Data collection and measurement

To test our conceptual model, we used an extended version of the process mining dataset by including additional variables. We describe the variables next. *Lead outcome.* The dependent variable lead follow-up refers to the actual follow-up of the salesperson. The variable is a binary measure where 1 refers to follow-up and value 0 for not followed-up. *Information load.* Information load refers to the total number of words mentioned in the system as inquiry details (customer request) and follow-up comments (of the call center representative). *Lead assignment quality and speed.* The lead assigning quality is measured using the number of attempts to assign a lead to a sales rep. Lead assigning speed is measured in hours. Following prior literature (e.g., Van Heerde, Gijsbrechts, & Pauwels, 2008) we correct for right–skewness of the distribution by log–transforming the speed measure. Both variables are inversely coded, as high quality means the least number of attempts and high speed means the lowest time till correctly assigned. *Uncertainty and familiarity.* Lead uncertainty (i.e., lead pre-qualification level) is measured on an ordinal scale where a “hot” lead is given value -3, a “warm” lead value -2, and a “cold” lead value -1, and value 0 for unknown or blank values. Customer familiarity (i.e., whether customer is already known by the company) is binary coded where value 1 means that a lead is from an existing customer and value 0 means that lead comes from a new customer.

3.4.1. Control variables

To ensure correct estimation we include several control variables. First, we include main effects, interaction effects, and quadratic terms for information load, speed, and quality to allow for correct estimation of main and moderating effects. Furthermore, we include a dummy for country as the sales force operates in two different countries. In addition, we include dummies for the specific sales channel. The dataset distinguishes between OEM, Consumer, and Professional segments. Furthermore, we include dummies for the sales segment; Office & Industry, Public, Retail & Hospitality, and ‘other.’ We included sales experience of the sales rep as a control variable to control for experience-based effects when making decisions whether or not to follow-up on a lead. Finally, we include a dummy for seasonal effects. We summarize the descriptive statistics and correlations in Table 3.

3.5. Endogeneity considerations

Although we include multiple control variables to rule out alternative explanations, the effect of lead assigning quality and speed on lead follow-up still may be spurious due to common unobserved factors (e.g., salesperson characteristics). Therefore, in line with Han, Mittal, and Zhang (2017), we address potential endogenous bias by running two auxiliary regression models. For the two auxiliary regression models we proceeded as follows. First, salespersons' selling portfolio may influence his or her time and resources allocations when making decisions for each incoming sales lead on whether or not to follow-up. To evaluate the effect of this potential source of endogeneity, we include average values of assignment quality, speed, and sales season as instrumental variables. Second, we ran two auxiliary regression models based on these instrumental variables. With regard to sales lead assigning quality, the multivariate F-test in a model with the endogenous variable (i.e., assignment quality) demonstrates that the instrumental variables are sufficiently strong, with an F-value of 49.35 ($d.f._1 = 2$; $d.f._2 = 745$; $p < .01$). The Sargan test shows that the exclusion restriction is satisfied ($p = .648$). The instrumental variables surpass the suggested thresholds, thereby representing good instrumental variables (Petersen, Kushwaha, & Kumar, 2015). The Durbin-Wu-Hausman test ($p = .617$) reveals that there is no concern of endogeneity for assignment quality (Antonakis, Bendahan, Jacquart, & Lalive, 2010).We employed the same process to test the potential endogeneity of assignment speed. The results again confirm that there are no concerns for endogeneity (F-value of 71.69, $d.f._1 = 2$; $d.f._2 = 745$; $p < .01$, Sargan test, $p = .275$, and Durbin-Wu-Hausman test of $p = .574$).

3.6. Model specification

We employ linear regression modeling with cluster-robust estimation in Stata 15.0 to account for the nested structure of data (i.e., sales leads are nested within salespersons). To test our main effect hypotheses, we first estimate three models — one model per dependent variable, i.e., Assigning Quality, Assigning Speed, and Lead Follow-up — by only including the control variables and (unconditional) main effects of the focal variables. Then, in a second step, we estimate the full models by adding the moderating effects. In doing so, we can test the impact of the moderating effects over and beyond the main effects estimated in step 1. The full models are specified with the following three equations:

Table 3
Descriptive statistics and correlation coefficients.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Lead follow-up																
2. Follow-up comments	0.023															
3. Lead assignment speed	−0.031	−0.122**														
4. Lead assignment quality	0.150**	−0.176**	−0.437**													
5. Lead uncertainty	0.100**	0.288**	−0.306**	−0.386**												
6. Customer familiarity	0.377**	0.043	−0.059	−0.004	0.082*											
7. Country	−0.118**	−0.025	−0.061*	0.049	−0.035	0.038										
8. Consumer	0.151**	−0.086**	0.086**	0.087**	0.021	−0.028	0.000									
9. OEM	−0.030	−0.024	0.037	−0.013	0.060	−0.010	−0.025	−0.008								
10. Professional	0.147**	0.013	0.047	0.100**	0.108**	0.081**	−0.033	−0.349**	−0.122**							
11. Office & Industry	0.210**	0.159**	−0.166**	0.021	0.134**	0.006	−0.084	−0.092*	−0.032	0.264**						
12. Public	−0.075**	−0.215**	0.231**	0.169**	−0.124**	0.055	0.198**	−0.105**	−0.043	0.347**	−0.525**					
13. Retail	−0.007	0.154**	−0.082*	−0.218**	0.189**	0.003	−0.153**	−0.051	−0.018	0.145**	−0.215**	−0.289**				
14. Experience	0.035	−0.044	0.041	0.033	−0.050	0.070	−0.015	0.039	0.041	0.003	0.022	0.007	−0.032			
15. Season	0.013	0.094**	−0.153**	−0.103**	0.157**	0.040	−0.005	−0.059	−0.035	−0.052	0.063	−0.129**	0.029	−0.176**		
16. Workload	−0.010	−0.032	0.045	−0.042	−0.056	0.025	0.070	−0.060	0.068	−0.020	0.093*	−0.030	−0.249**	−0.104	0.099**	
Mean	0.25	81.66	−198.12	−1.68	1.71	0.04	0.81	0.021	0.003	0.85	0.28	0.41	0.11	5.60	0.31	65.11
Standard Deviation	0.43	77.18	656.316.31	0.94	1.11	0.19	0.39	0.144	0.051	0.36	0.45	0.49	0.31	4.63	0.46	53.61

Notes: * $p < .05$, ** $p < .01$ (two-tailed significance test), $n = 754$ Leads.

$$QUAL_i = b_0 + b_1TIL_i + b_2TIL_i^2 + b_3FAM_i + b_4UNC_i + b_5(TIL_i \times FAM_i)_i + b_6(TIL_i^2 \times FAM_i)_i + b_7(TIL_i \times UNC_i)_i + b_8(TIL_i^2 \times UNC_i)_i + +b_{8+q}Control_i + \varepsilon_i, \quad (1)$$

$$SPEED_i = \delta_0 + \delta_1TIL_i + \delta_2TIL_i^2 + \delta_3FAM_i + \delta_4UNC_i + \delta_5(TIL_i \times FAM_i)_i + \delta_6(TIL_i^2 \times FAM_i)_i + \delta_7(TIL_i \times UNC_i)_i + \delta_8(TIL_i^2 \times UNC_i)_i + \delta_{8+q}Control_i + \alpha_i, \quad (2)$$

$$LFU_i = \zeta_0 + \zeta_1TIL_i + \zeta_2TIL_i^2 + \zeta_3QUAL_i + \zeta_4QUAL_i^2 + \zeta_5SPEED_i + \zeta_6SPEED_i^2 + \delta_7(QUAL_i \times SPEED_i)_i + \zeta_{8+q}Control_i + \nu_i, \quad (3)$$

where QUAL = sales lead assigning quality, SPEED = sales lead assigning speed, TIL = information load, FAM = customer familiarity, UNC = uncertainty, and LFU = lead follow-up. ε_i, α_i, and ν_i are the idiosyncratic error terms for salesperson i. Control is a vector of the covariates, where $q \in N = \{1, 2, \ldots, 8\}$.

3.6.1. Robustness checks

We assessed the robustness of our results to (1) multicollinearity, (2) potential omitted variables. First, we computed variance inflation factors (VIFs) for each independent and control variables. The maximum VIF is 2.41, well below the threshold value of 10 (Hair et al., 2010), thus indicating no multicollinearity issues in our results. Second, to test for potential omitted variables in our results, we implemented a Ramsey regression specification-error test (RESET) for omitted variables (Ramsey, 1969). The Ramsey test was not significant ($z = 0.589$, $p > .10$), thereby alleviating concerns about potential omitted variable bias in our results.

3.7. Results and discussion

3.7.1. Main effects

As Table 4 shows, information load is negatively related to lead assignment quality (Model 1: $b_1 = -0.166$, $p < .01$) and lead assignment speed (Model 2: $\delta_1 = -1.063$, $p < .01$), in support of H_{1a} and H_{1b}. In addition, as expected we find negative quadratic effects of quality on lead follow up (Model 3: $\zeta_4 = -0.098$, $p < .05$) and speed on lead follow-up (Model 3: $\zeta_6 = -0.086$, $p < .05$), thereby providing support for H_{4a} and H_{4b}.

As Fig. 2 illustrates, there is an intrinsic relationship between quality and speed and how it affects lead follow-up. Interestingly, it appears that quality and speed need to be aligned to ensure lead follow-up. In contrast, mismatching between speed and quality, that is either low speed and high quality or low quality and high speed, both lead to suboptimal performance. Yet, of these two 'mismatching' approaches it seems that speed should be preferred over quality when assigning leads.

3.7.2. Moderating effects of customer familiarity

With respect to the moderating role of customer familiarity, Table 4 reveals that the negative effect of information load on lead assigning quality diminishes as salesperson's customer familiarity increases (Model 4: $b_5 = 0.144$, $p < .01$), in support of H_{2a}. Likewise, the negative effect of information load on assignment speed weakens as salesperson's customer familiarity increases (Model 5: $\delta_5 = 0.820$, $p < .01$), in support of H_{2b}. We also find that this effect is nonlinear (Model 5: $\delta_6 = -0.299$, $p < .01$). Fig. 3, Panel A and B plot the interaction effects to facilitate the interpretation of our findings. The plots provide the results for values 1 standard deviation below and above the mean of the independent variable and the moderator. As the plots in both Panel A and B show, the slopes of the relationships

Table 4
Hypothesis testing result.

	Main-effect models									Full models								
	Model 1: Assigning quality			Model 2: Assigning speed			Model 3: Lead follow-up			Model 4: Assigning quality			Model 5: Assigning speed			Model 6: Lead follow-up		
	b		SE	b		SE	b		SE	b		SE	b		SE	b		SE
Constant	−1.578	**	0.196	−4.041	**	0.312	−16.85	**	0.377	−1.785	**	0.225	−3.975	**	0.323	−16.53	**	0.416
Direct effects																		
TIL	−0.166	**	0.042	−1.063	**	0.216	−0.010		0.160	0.093		0.063	0.049		0.157	0.028		0.154
TIL^2	0.122	**	0.042	0.812	**	0.191	0.072		0.140	−0.055		0.047	0.019		0.119	0.054		0.132
QUAL							−0.471	*	0.202							−0.432	*	0.194
$QUAL^2$							−0.098	*	0.047							−0.149	*	0.065
SPEED							0.437	**	0.107							0.362	**	0.108
$SPEED^2$							−0.086	*	0.041							−0.145		0.085
Moderators																		
FAM										−0.098		0.088	0.331		0.235			
UNC										0.296	**	0.047	0.425	**	0.112			
Interaction effects																		
TIL × FAM										0.144	**	0.043	0.820	**	0.103			
TIL^2 × FAM										−0.005		0.037	−0.299	**	0.074			
TIL × UNC										−0.035		0.025	0.272	**	0.081			
TIL^2 × UNC										−0.071	**	0.018	−0.053		0.050			
QUAL × SPEED																0.291		0.177
Controls																		
Country	−0.256	**	. 079	0.079		0.103	−0.712	*	0.312	−0.234	**	0.063	0.038		0.171	−0.663	*	0.314
Consumer	0.608	**	0.231	1.619	*	0.734	18.195	**	0.798	0.697	**	0.219	1.231	*	0.596	17.799	**	0.770
Professional	0.029		0.219	0.063		0.280	16.128	**	0.339	0.176		0.211	0.132		0.276	15.726	**	0.338
Office & Industries	−0.084		0.110	0.906	**	0.225	0.649	*	0.259	−0.133		0.103	0.719	**	0.230	0.643	*	0.269
Public	0.396	**	0.108	0.977	**	0.171	−0.037		0.273	0.299	**	0.085	0.510	**	0.162	−0.042		0.273
Experience	0.000		0.007	−0.006		0.027	0.017		0.022	−0.002		0.007	−0.010		0.021	0.015		0.023
Sales season	−0.213	**	0.081	−0.259		0.241	0.134		0.145	−0.099		0.066	0.010		0.152	0.133		0.146
Workload	−0.059		0.030	−0.214		0.127	−0.003		0.107	−0.061		0.033	−0.213	**	0.078	−0.013		0.106
Sample	754			754			754			754			754			754		
R^2	0.101			0.119			0.150			0.187			0.378			0.155		

Note: $^{*}p < .05$, $^{**}p < .01$ (unstandardized coefficient; two-tailed significance tests are tested) TIL = total information load (sum of inquiry details and follow-up comments); QUAL = quality (number of attempts); SPEED = speed (time till correct assign); UNC = uncertainty (qualification level); FAM = familiarity (customer familiarity); SE is robust standard error based on clustered sandwich estimator. Since 'Assigning quality' is a count variable that is over-dispersed we also re-ran the analyses using negative binomial regression estimation. The findings are similar to those reported in this table thereby corroborating the robustness of our findings.

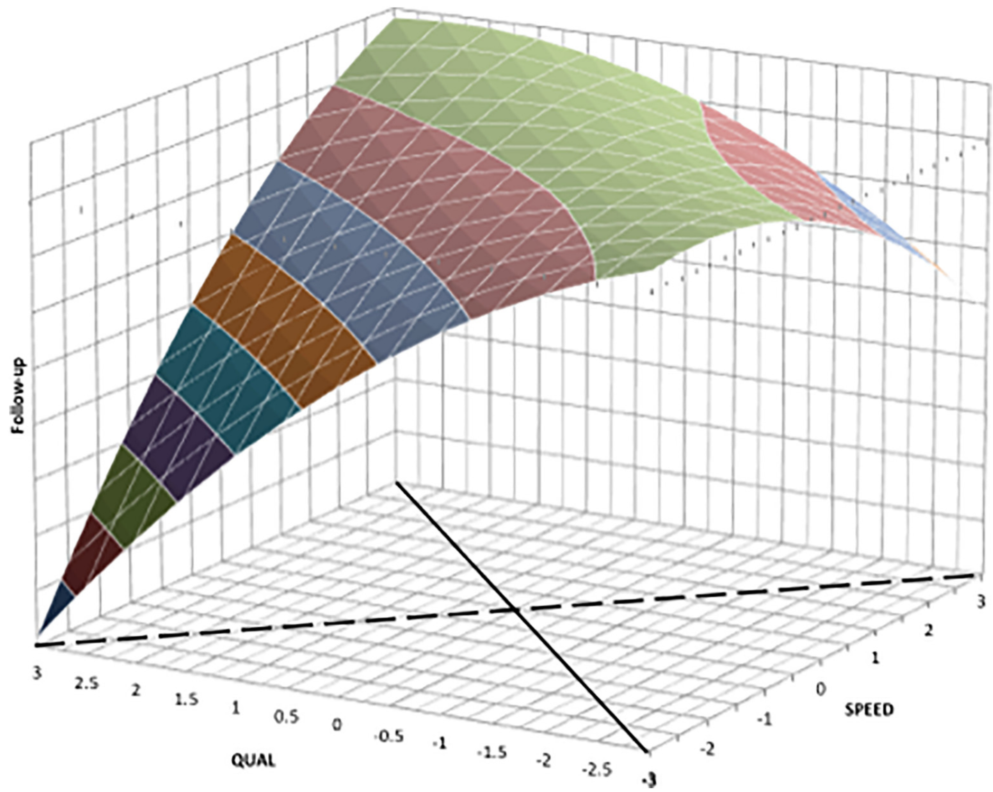


Fig. 2. Relation between speed, quality and follow-up.

between information load and lead assigning quality and speed are becoming increasingly positive for higher levels of customer familiarity. So, marketing people leverage the available text-based information more when they are dealing with existing customers, which leads to faster lead assignment in fewer attempts. In contrast, for new customers we see that information has no predictive power in terms of how many attempts are needed to assign the lead, as indicated by the almost flat line in Fig. 3, Panel A. In addition, for new customers we see that having more textual information available leads to slower lead assignment as indicated by the negative slope in Fig. 3, Panel B. This suggests that marketing people give leads from new customers accompanied with relatively much textual information lower priority. More textual information may be an indication that the lead needs more processing, but from the current analyses we cannot affirm this line of reasoning.

3.7.3. *Moderating effects of lead uncertainty*

For the moderating effect of lead uncertainty Table 4 shows that the linear negative effect of information load on lead assigning quality is not affected by uncertainty (Model 4: $b_7 = -0.035$, $p = n.s.$), thereby providing no support for H_{3a}. Yet, we do find a negative moderating effect for the nonlinear relationship (Model 4: $b_8 = -0.071$, $p < .01$). As Fig. 4, Panel B illustrates, we observe a diminishing effect of information load on quality for higher levels of information load when uncertainty is high, indicating an optimal level of information load given high uncertainty. For low lead uncertainty more information does lead to higher quality processing, that is, marketing needs fewer attempts.

Furthermore, the negative linear effect of information load on assignment speed decreases when uncertainty increases (Model 5: $\delta_7 = 0.272$, $p < .01$), in support of H_{3b}. As Fig. 4, Panel B illustrates the slope of the relationship between information load and lead assignment speed becomes more positive for higher levels of uncertainty. So, in line with our hypotheses marketing employees seem to be more willing to deliberately process available information when lead uncertainty is high, thereby reducing the time to assign the leads.

3.7.4. *Overall discussion*

The explanatory analyses confirm most of our hypotheses but also provide some more nuanced insights. The first take-away is regarding the importance of lead assignment speed and quality and their interrelationship. The results show that salespeople are most likely to follow-up on assigned leads if there is some match between the speed of assignment and the number of attempts needed to assign the lead (see Fig. 2). Although we can only speculate about the exact nature of the salesperson's judgment process when assessing incoming leads, we do see that a mismatch between speed and quality (i.e., slow assignment—few attempts; quick assignment; many attempts) will seriously lower the probability that salespeople will follow up the lead. Thus, over and beyond other factors—including factors such as the textual information provided with the lead (i.e., content), a salesperson's experience, workload, and sales territory—marketing's processing of leads in terms of speed and quality provides important cues for a salesperson's lead follow-up judgment.

Second, in line with prior research (e.g., DeCarlo & Lam, 2016), the results show that new customers are processed differently from existing customers. For existing customers, if information load is relatively low, it takes more time and attempts to assign the lead to a salesperson. On the other hand, if more information is available, then leads are assigned more quickly and with fewer attempts. For new customers, this is different. Although information does not seem to affect the number of attempts to assign the lead, it does negatively relate to speed, such that more information associates with more lead processing time. It is likely that leads coming from new customers are seen as laboursome and risky (DeCarlo & Lam, 2016), especially if accompanied by relatively more text-based information. It might be that these customers have more complicated inquiries and are more difficult to match with a qualified salesperson. Regardless of the reasons, given the negative relationship between information load and speed for new customers, it seems to confirm our reasoning that inquiries from new customers receive less

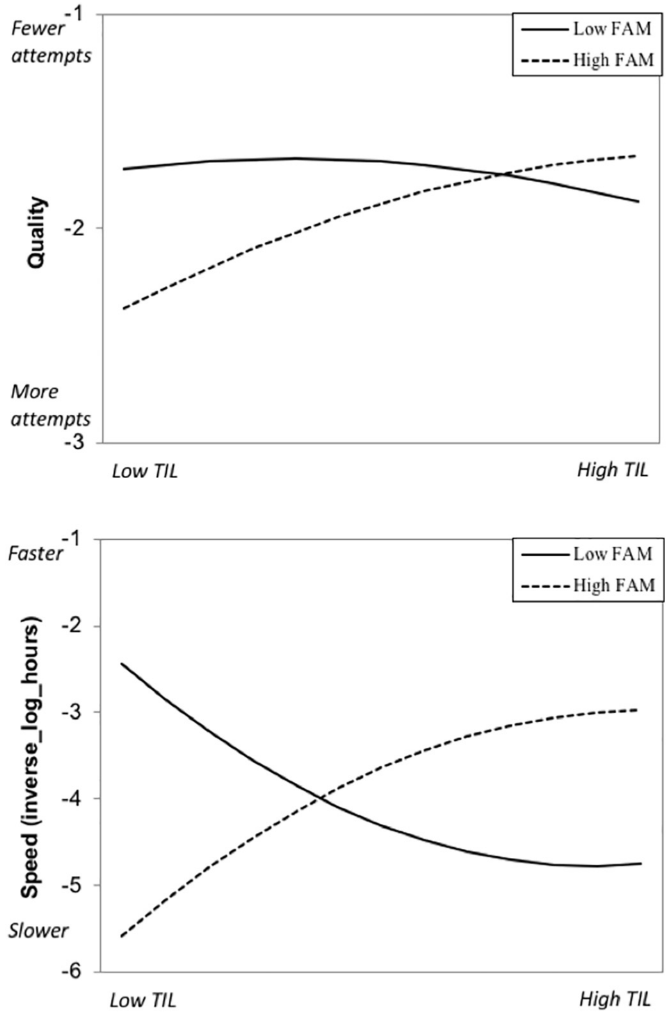


Fig. 3. Relation between information load, familiarity, and lead assigning process outcomes.

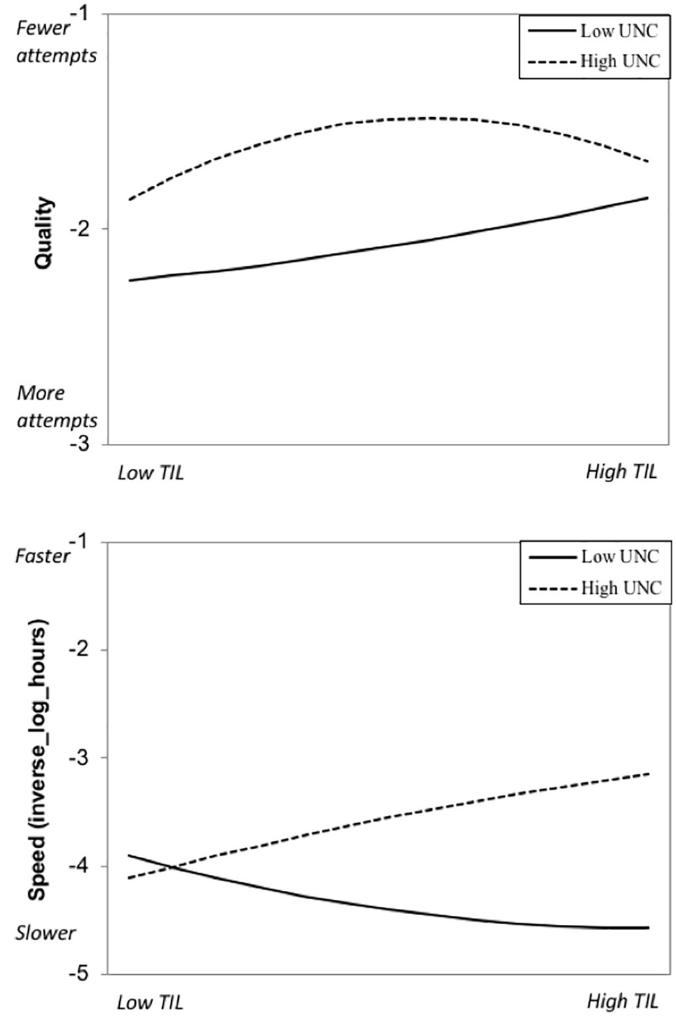


Fig. 4. Relation between information load, uncertainty, and lead assigning process outcomes.

attention and lower priority.

Third, the uncertainty level assigned to an incoming lead also effects how people process the lead. Overall, we see that high uncertainty associates with a positive relationship between information load and assignment speed (see Fig. 4, Panel B). This suggests that marketing is prioritizing more uncertain, 'colder' leads where available information is utilized to reduce uncertainty. Interestingly, for these 'colder' leads the quality of assignment is deteriorating after some point, where higher levels of information load require more attempts (see Fig. 4, Panel A). It may relate to the complexity of the inquiry, whereby marketing needs more attempts to find a qualified salesperson.

Compared to 'colder' leads, 'hotter' leads—perhaps counter-intuitively—are assigned less quickly and with relatively more attempts. Related research on new product selling shows that when salespeople perceive new products as substantially better than existing products they tend to allocate less attention and effort to these products because these products are expected to 'sell themselves'(Ahearne, Rapp, Hughes, & Jindal, 2010). In a similar way, hot leads may be perceived as 'done deals' where marketing (and sales) employees may give these leads a lower priority, assuming that customer's buying readiness is so high that they do not need a special treatment or fast processing. Higher information load seems to enhance this effect by providing more confirmation that the lead is hot. This is consistent with research that shows that in the dynamic pursuit of multiple targets over time, people tend to allocate more time and effort to goals that are furthest from attainment (e.g., Schmidt and Dolis 2009; Lam, DeCarlo, & Sharma, 2019).

Finally, we see that uncertainty related to customers is processed differently than uncertainty related to the lead itself. Whereas customer-related uncertainty relates to lower prioritization, lead-related uncertainty leads to higher prioritization. People may have different associations for customers (e.g., account, farming, potential for losses) than for leads (e.g., event, hunting, opportunity) which may trigger different decision-making heuristics or motivational states (e.g., DeCarlo & Lam, 2016). For instance, it is widely acknowledged that retaining existing customers is five times cheaper than attracting new customers (e.g., Wertz, 2019), so hunting for new customers likely goes at the expense of relationships with existing customers. For lead-related uncertainty it seems that people rely more on an effort based heuristic where more value is attributed to those tasks that require more effort (Kruger, Wirtz, Van Boven, & Altermatt, 2004). For companies it is important to understand how speed and quality in decision-making processes affects bottom-line performance.

3.8. Development and validation of design rules

3.8.1. Design rules: CIMO-logic

Building on the insights from the exploratory and explanatory analyses, we can draw a number of conclusions which can be formalized into what could be labeled as design rules. The design rule specifies the mechanism through which field problems link to interventions and outcomes. In specific, we follow the so-called 'CIMO-logic' (Denyer et al., 2008), which involves a combination of a problematic context (C), for which the design proposition suggests a certain intervention type (I), to produce, through specified generative mechanisms (M), the intended outcome(s) (O). Design rules provide managers information on which action to execute, under which condition(s), to produce what outcome, and offer some understanding of why this occurs. Design rules provide a vehicle for addressing fragmentation and increasing the chances of application beyond academia as they can be easily tested in other settings as well, unlike context specific instantiations (Denyer et al., 2008).

3.8.2. Proposed interventions

Based on our exploratory and explanatory analyses we identify four interventions, which we describe next:

1. Emphasize the importance of new customers as being equally important to existing customers.

In business-to-business environments, company performance hinges on the generation of sales by maintaining and enhancing existing customer relationships and attracting new customers. Managers can prevent a success trap in farming existing customers (Lam et al., 2019) by hiring salespeople with specific motivational traits (e.g., promotion focus), signaling the equal importance of both new and existing customers (e.g., via training or role modeling), and by implementing customer acquisition-based compensation plans (DeCarlo & Lam, 2016).

2. Highlight that there are no 'sure hits' in B2B solution selling; even if the outset looks promising (e.g., lead is 'hot') it is important to carefully assess the incoming lead

Managers need to make sure that subordinates do not fall into the trap where they underinvest in goals that are closest to attainment because of over-confidence or due to the false belief that they can reduce effort. To prevent such biases, managers can ask subordinates to reflect on their choice, thereby promoting the use of available information in a more deliberate manner, for instance by asking for a 'second-order judgment' about the first judgment (Arkes, 1991) — that is, by asking subordinates how confident they are about the first judgment (e.g., hot, warm, cold) and requesting for an explanation.

3. Prioritize speed of assigning leads over reducing attempt to assign leads.

The results show that when people need to choose between quality and speed, it is better to choose speed over quality. Quickly assigning a lead to a salesperson ensures that leads do not unnecessarily delay and devaluate in the process. Moreover, it may lead to a trial-and-error approach where uncertainty is reduced more quickly (e.g., Read et al., 2009).

4. Make sure that salespeople quickly provide feedback regarding their assessment of the assigned lead (i.e., provide feedback on whether they follow-up, give back, or reject a lead).

Although this study focused on the marketing rep's part in lead assignment speed and quality, delays also occur due to the receiving part's lack of responsiveness. That is, salespeople may fail to provide fast feedback regarding their follow-up actions. Managers can govern such behaviors in several ways, for instance by making explicit rules, by nurturing norms, by encoding protocols in the IT systems, and by implementing specific incentives.

3.8.3. Proposed design rules

Table 5 depicts the design rules or solution artefact, which we label *information-based lead assignment of B2B inquiries*. The solution combines well-known research-based principles from decision-making literature and operations management literature with practice-based insights from our field study. The first two interventions specify how governance should be focused on preventing biases that lead to unthoughtful, automatic processing of leads. More specifically, the rules aim to prevent (i) biases that lead to overemphasizing existing over new customers (e.g., Nijssen, Guenzi, & Van der Borgh, 2017) and (ii) biases that lower effort on promising leads, for instance because the presumption is that a lead 'will sell itself' (e.g., Ahearne et al., 2010). The idea is that by making employees aware of the importance of each and every incoming lead, all available information is processed in making an assignment decision and if no information is available that leads are quickly assigned to ensure that somebody follows up. The last two interventions are rather straightforward and specify the design of a governance system that motivates people to quickly process incoming leads, thereby reducing buffers and variation in processing time. Together the four interventions should govern 'good behavior' of employees and ensure a higher follow-up ratio.

3.8.4. Validation of design rules

The final step of a design-based science project involves the testing of the solution, or in our case, verifying the design rules, which then may trigger a new round of investigations (for instance see Groop, Ketokivi, Gupta, & Holmström, 2017). Many approaches exist to test such design rules. Examples include simulations, action research, and field experiments. In our case we were limited to test the design rules via focus group discussions and via expert testing, a so-called alpha test (Van Aken, 2004). The alpha test revealed that the proposed design rules showed face validity. However, some experts indicated that there are some important assumptions that are important to make explicit. First, it is important that the pre-qualification of leads is considered trustworthy. This allows people to quickly filter interesting opportunities and remove those inquiries that are not of interest. For instance, customer complaints need to be redirected to customer care, and standard request can be diverted to trade partners. A second important aspect is the workload of involved employees. It is possible that people reject promising leads because of time constraints. We checked this line of reasoning by including workload as a control and we found no effects, thus corroborating our findings.

3.8.5. Boundary conditions of the design rules

While the proposed design rules show face validity, its practical relevance and validity only can be proven during actual implementation. So, the boundary conditions of the proposed design rules are that they may only be relevant for the current context. In addition, the theoretical lenses used to frame the problem also guide the solution development. Using other lenses may lead to other, perhaps better solutions. In the limitation section we provide other boundary conditions of the current study and its artefacts. Important to note in this respect is that researchers as designers not only learn how to design, but also learn from implementing their designs (Dunbar & Starbuck, 2006). Design efforts should be viewed as experiments, and also can be tested as such. In addition, it is good practice to look for contraindications (Van Aken, 2005), which indicate under which conditions it is advisable not to perform a particular intervention, either because it leads to lower desired outcomes or because it has adversary side-effects (i.e., a negative effect on another outcome of interest; e.g., higher productivity but lower quality). Future research could examine the boundary conditions of the design rules proposed in this study using beta testing.

4. Discussion

The goal of this study was to examine the so-called sales lead black hole, identify its existence, analyze causes and effects, and provide a

Table 5
Information-based lead assignment of B2B inquiries.

	Decision-making under uncertainty	Theory of even, steady flow	Combinatorial innovation: information-based lead assignment of B2B inquiries
Context	Assigning leads with limited available information	How can leads be pushed through the sales funnel with as little disruptions as possible?	How should sales leads be assigned in a field sales setting where both available information and pre-qualification level are diverse, and some inquiries are from new customers while others are from existing?
Intervention	Interventions 1 and 2, at the abstract level: develop a governance system where people make judgments based on available information.	Interventions 3 and 4, at the abstract level: create a system with speed related targets to reduce chance that leads are not actively processed.	The four interventions together, contextualized into the B2B sales setting.
Mechanism	Avoid biases (e.g., demotivation, lower prioritization, or distrust) by deliberately using information when available and quickly learn when little information is available.	Preventing devaluation of leads, that is by not processing them quickly enough, makes it more likely that flow is ensured.	Focus on deliberate and fast processing of leads results in more effective lead (assignment) processing management.
Outcomes	Preventing mismatching of speed and quality; i.e., do not assign slow with high quality OR quick with low quality.	Reduced average time (and variation) to assign a lead.	Improved marketing generated lead follow-up.

solution for managers on how to deal with the problem. In doing so, we extend marketing research (MacInnis, 2011) and provide scholars with a template for conducting design-based science, which goal is to connect field problems with academic knowledge to create problem solving knowledge.

4.1. Theoretical implications

This study is the first to explicitly show the existence of the sales lead black hole in an academic study. Although many studies report the existence of the sales lead black hole, little evidence was brought to the table. By examining the lead assignment process at a large product-solution provider we were able to show the significance of the problem, that is, in our field study the sales reps followed up less than 15% of the marketing generated leads. A number that is far below the 30% reported elsewhere. In addition, our exploratory analyses revealed that current literature on the phenomena does not provide much direction for managers on how to deal with the issue, which therefore warranted an in-depth exploratory analysis at our sponsor company.

Analyses of interview data and process mining revealed that especially the lead assignment process proved to be a large bottleneck in the lead management process, which was the focus of our further analyses. The lead assignment process is the point where marketing assigns identified leads to sales representatives. The speed and quality of this lead assignment process determines actual lead follow-up by salespeople. To better understand the underlying mechanisms, we conducted an explanatory analysis. Building on the insights from the exploratory analyses and literature on decision-making under uncertainty and operations management, we were able to build and test a conceptual model. The analysis was the first to explicitly examine the lead assignment process in a B2B setting. Although previous studies examined, for instance, motivations, opportunities, and abilities of salespeople in explaining their allocation of time (Sabnis et al., 2013), we were the first to tease out the impact of the lead assignment process on actual lead follow up.

Second, we introduce design science to the field of marketing and sales research. While much research focuses on examining marketing and sales problems in the field most of these studies focus on explaining, describing, exploring, or predicting phenomena and their relationships with each other. However, most of these studies do not provide solution artefacts or details how to create them. In this paper, building on design science, we introduce a research model that explains the process of creating such artefacts. Adopting pragmatism as a scientific approach, it allows the inclusion of inductive, deductive, and abductive reasoning and qualitative and quantitative approaches. That it, design science research clearly builds on the rich extant body of knowledge already available in marketing science to change the status quo.

Third, by formulating design rules this study not only offers normative guidelines for managers but also provides testable propositions that can be tested by scholars in other settings (beta testing), using for instance field experiments, simulations, or action research. As such, design rules provide a vehicle for closing the relevance-rigor gap as it provides a common lexicon for both managers and scholars when talking about how to examine and solve practitioner problems.

4.2. Managerial implications

Based on the explanatory analysis we develop design rules that guide managers in the field in creating a contextualized solution. Taken together, the design propositions contribute to academic literature to improve the follow-up of marketing generated leads by sales reps. For instance, the solution contributes to the resolution of biases between marketing and salespeople when working together (e.g., Homburg & Jensen, 2007) by proposing a way to make salespeople aware of each and every incoming lead and fostering the quick processing of these leads. In addition, contradicting some previous studies emphasizing the benefits of a (1) trial-and-error approach or (2) rational, decision making approach when operating under high levels of uncertainty (e.g., Read et al., 2009), our study points out that people generally do not perceive either decision-making heuristic as very trustworthy. Our interpretation is that these two heuristics associate with negative attributions, for instance, '*it took too long probably because the lead is not worth pursuing in the first place*', or '*marketing does not have a clue what to do with this lead, and therefore assigned it to me*'. Although these two heuristics may be considered the best option from a decision-making perspective, from the receiving end, that is, the salesperson it certainly may not come across as a good approach to reach a decision. Finally, by combining softer, human centered aspects with harder, operation management related aspects we believe we come to a more nuanced perspective on decision making in the lead assignment process.

4.3. Methodological considerations, limitations, and future research

In sum, in this study we helped a globally operating company to find solutions for the perennial sales lead black hole. The solutions, jointly developed with practitioners, combines decision-making theories and the theory of even, steady flow in an attempt to allocate leads to sales representatives more effectively. Although we think our research has clear merits, there are several limitations too. Some of them may provide fruitful avenues for future research.

First, the applicability of the provided solution design is limited to the problem context of this study, that is a business-to-business product-solution provider of a large multinational. Although narrowing the focus of our study helped control for potentially confounding factors, it also limited the generalizability of results. We hold that our sample profile is typical for firms—with field salesforces selling complex offerings to business customer—for many industries, such as machinery, chemicals, plastic materials, equipment and supplies, and pharmaceuticals. Yet, it is likely that in a business-to-consumer context other issues play a role, thereby requiring a different solution. As Smith et al. (2006) show, in their context visits are planned and, as a result sales rep follow-up is high – partly because these sales reps do not have many self-generated leads. While this does not affect our recommendations on how to analyze and solve the sales lead black hole, future research might explore boundary conditions.

Second, our solution is developed in a context where marketing is responsible for generating part of the opportunities and, as such, needs to convince sales representatives of the value of the marketing generated leads over and above those generated by sales reps themselves. Future research needs to consider the total portfolio of opportunities to fully understand why salespeople follow-up on marketing generated leads (Sabnis et al., 2013).

Third, in our model, we only investigate the word load rather than content. If the information content is very insightful and thoughtful, the results may be different. Recent studies have used text-mining method to analyze the impact of information content. For example, Lee and Bradlow (2011) use text-mining algorithms to analyze the effect of online customer reviews on market structure. Future research could substantiate the effects of information content, not only information load. In addition, future research should investigate the relationship between the text-based content and our concept of lead uncertainty. While we treated word count and lead pre-qualification as two uncorrelated constructs, the actual text-based content may be the predictor of lead pre-qualification. We urge future research to explore this relationship more in-depth. Fourth, although we control for several variables in our models and show that our findings are robust to unobserved heterogeneity and endogeneity, future research could include other explanatory variables such as a salesperson's capability to follow up on a sales lead.

Finally, as with all designs, there is not one ultimate solution for a particular field problem. So, alternative solutions are feasible, perhaps even superior under certain conditions. In line with this, we urge future research to explore alternative solution artefacts and compare the effectiveness of these solution artefacts in addressing the identified problem class, that is the sales lead black hole. In the end, we consider this the core aim of any scientific field that aims to improve the body of knowledge for managers in the field.

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