COGNITIVE BIASES IN INFORMATION SYSTEMS RESEARCH: A SCIENTOMETRIC ANALYSIS

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Abstract

Human cognition and decision-making related to information systems (IS) is a major area of interest in IS research. However, despite being explored since the mid-seventies in psychology, the phenomenon of cognitive bias has only recently gained attention among IS researchers. This fact is reflected in a comparatively sparse set of mostly disconnected publications, sometimes using inconsistent theory, methodology, and terminology. We address these issues in our scientometric analysis by providing the first review of cognitive bias-related research in IS. Our systematic literature review of 12 top IS outlets covering the past 20 years identifies 84 publications related to cognitive bias. A subsequent content analysis shows a strong increase of interest in cognitive bias research in the IS discipline in the observed timeframe, yet uncovers a highly unequal distribution across IS fields and industry contexts. While previous research on perception and decision biases has already led to valuable contributions in IS, there is still considerable potential for further research regarding social, memory and interest biases. Our study reveals research gaps in bias-related IS research and highlights common practices in how biases are identified and measured. We conclude with promising future research avenues with the intent to encourage cumulative knowledge-building.

Keywords: Decision-Making, Cognitive Biases in IS, Scientometric Analysis.

1 Introduction

Human decision-making is one of the main areas of interest in information systems (IS) research (Goes, 2013). A prominent example is the extensive stream of technology acceptance research that aims to explain and predict the IS users’ adoption and usage decisions (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). Decision Support Systems (Shim et al., 2002; Arnott and Pervan, 2005; Arnott and Pervan, 2008) and IT Outsourcing (Dibbern et al., 2004; Gonzalez et al., 2006; Lacity et al., 2010) are other examples of areas that extensively explore decision-making. One commonality of these research streams is their collective reliance on theories which were originally adopted from psychology research. For example, technology acceptance research such as Davis’ (1989) Technology Acceptance Model and its variations all draw on Fishbein and Ajzen’s (1975) Theory of Reasoned
Action. The successful history of each of the above mentioned research streams in IS shows the value of relying on psychological knowledge in order to gain insights into a wide variety of IS related phenomena (Goes, 2013). In all these cases, the body of psychological knowledge has facilitated IS researchers to advance the discipline and to provide valuable recommendations for practitioners.

One particular phenomenon from psychology research that is related to human decision-making has recently gained attention in IS research—the so called cognitive biases. Being a side effect of the application of heuristics, cognitive biases are defined as systematic errors in human decision-making (Wilkinson and Klaes, 2012). As described by Simon (1990, p.11), heuristics are “methods for arriving at satisfactory solutions with modest amounts of computation.” Heuristics are sometimes also referred to as rules of thumb. The results of cognitive biases are objectively nonrational decisions that often lead to suboptimal outcomes for the decision-maker or other individuals who are affected by the particular decision (Wilkinson and Klaes, 2012). The application of these behavior-influencing cognitive biases, similar to other psychological theories and theoretical concepts, hold enormous potential to apprise and supplement IS research. IS contexts in particular are characterized by increasing information richness and interactive decision-making as can be seen in settings such as crowdsourcing and collective intelligence, electronic marketplaces, personalization and recommendation systems. Issues such as privacy, trust and security, for example, which arise from these environments, are closely connected to behavioral aspects and are thus potentially prone to cognitive biases (Goes, 2013). First research results also show the direct value of applying insights on cognitive biases in IS (e.g. Arnott, 2006; Kim and Kankanhalli, 2009). Finally, the seemingly increasing interest in cognitive biases among IS researchers can be also seen as evidence for this phenomenon being a welcomed innovation in the discipline (Browne and Parsons, 2012).

However, while the concept and resulting insights on cognitive biases have been around for almost 40 years now (Tversky and Kahneman, 1974), research on cognitive biases in IS has remained comparatively sparse. We thus agree with Browne and Parsons (2012) who advocate for more research in this direction. In addition to being sparse, research studies on biases in IS have also remained loosely connected to one another and have largely been inconsistent in their use of terminology and methodology (e.g. Mann et al., 2008). To the best of our knowledge, there is to date no comprehensive literature review of research on cognitive biases in IS, on which authors could build their work upon. As a result, it remains difficult to find links between existing research studies and to identify possible avenues for future research. This, in turn, makes it difficult to contribute to cumulative knowledge-building in IS.

In the present study, we aim to address these issues and thus close a gap in the research on cognitive biases in IS. In order to achieve this goal, we examine the following two research questions:

RQ1: What is the current state of research on cognitive biases in the IS discipline?

RQ2: What are promising avenues for future research on cognitive biases in the IS discipline?

In the course of answering these research questions, we make several contributions. First, we provide a systematic literature review—a scientometric analysis—of research dealing with cognitive biases in IS. By combining our findings on cognitive biases with information about research fields, applied research methods, and industry contexts, our review provides a comprehensive picture of the current state of research on biases in IS. On the one hand, this allows us to identify areas in which biases have already received substantial acknowledgement by researchers. On the other hand, we are able to disclose existing areas with no or only few publications on biases. Based on these research gaps, we are able to provide well-grounded and theory-guided avenues for future research that have the potential to further advance the explanatory and predictive capabilities of the IS research discipline.

The remainder of this study is organized as follows. In section 2, we report on the procedures of our scientometric analysis. Its results are presented in section 3. In section 4, we give a summary of our overall findings, discuss the results from our analysis, and provide avenues for further research.
2 Scientometric Analysis

Leydesdorff (2001) defines scientometrics as “the quantitative study of scientific communication” (Leydesdorff, 2001, p.1), while Lowry et al. (2004) consider it “the scientific study of the process of science”. Lewis et al. (2007) recommend scientometric studies to advance the ongoing evaluation and improvement of an academic discipline. Scientometric studies have been conducted on a broad range of topics in IS research such as on IS as a reference discipline or the epistemological structure of the IS field in general (Grover et al., 2006; Kroenung and Eckhardt, 2011). In this study, we selected the scientometric approach for its structured, systematic procedure, compared to, for example.

Following Pateli and Giaglis (2004), in the first step, we defined the scope of our search. It can be characterized along three dimensions: (1) the outlets, which are covered by our search, (2) the relevant time span, and (3) the search terms used. In our search procedure, we then performed two separate rounds: initial search and subsequent (forward and backward) search (Webster and Watson, 2002; Yang and Tate, 2012). In a third step, we conducted a content analysis (Krippendorff, 2004) to examine all relevant identified papers. In the remainder of this section, we elaborate on the aforementioned steps of the scientometric approach: scope of literature search, search procedure, and procedure of analysis.

2.1 Scope of literature search


From these publications, we included in our search completed research papers and research-in-progress papers. Within this scope, we considered any research published from January 1992 to October 2013, as well as forthcoming papers, if available. We considered the past 20 years of IS research to be a sufficient time frame in order to enable us to draw a comprehensive picture of the development of research on cognitive biases in IS.

To develop the set of relevant search terms for our review, we started with the terms bias and non-rational behavior. From basic literature on cognitive biases, we extracted further, more specific terms, such as framing or anchoring until theoretical saturation was achieved (Auerbach and Silverstein, 2003). After an expert validation of the collected search terms, we ended up with an exhaustive set of 120 search terms1.

1 The complete list of employed search terms, including references for each search term, can be obtained from the authors upon request.
2.2 Search procedure

In the first round, we scanned the abovementioned 12 journals and conference proceedings. Depending on the type of publication, we relied on the databases of EBSCOhost, Palgrave Macmillan, Science Direct and SpringerLink. To identify relevant forthcoming papers, we also checked the forthcoming sections of each journal website, if available. The inclusion criteria for a paper to be considered relevant was one or more of our search terms being in its title, abstract or among its self-reported keywords. This first search round resulted in 160 hits. The full texts of these 160 papers were then manually scanned for irrelevant articles. Articles that did not address the bias phenomenon in the sense of cognitive biases (e.g. discussions of the selection bias in statistical analysis of quantitative empirical research) were excluded (Yang and Tate, 2012). After this step, 84 relevant articles remained.

To ensure integrity of our search, we then conducted a second round: a forward and backward search (Webster and Watson, 2002). Backward search refers to reviewing additional sources that have cited the relevant articles and determining which of the newfound articles should be included in the review. For our forward search, we used Reuters’ (2013) Web of Science.

Both our forward and our backward search were confirmatory and thus had the same scope as round one. No additional relevant articles were found during this second round. This is a confirmation of the comprehensiveness of our first search round. The final number of relevant articles used for the following analysis thus remained 84 (the 84 articles included in our scientometric analysis are marked with * in the References section). Based on the scope of our search, the total number of searched articles was 12,990. The number of publications dealing with biases (n=84) was thus less than 1% of all articles in our search scope.

2.3 Procedure of analysis

The 84 identified papers were examined based on 12 factors. These are: (1) year of publication, (2) outlet, (3) biases studied, (4) bias category (5) examined research field, (6) industry context, (7) applied research method, (8) approach of measuring the cognitive bias of interest, (9) theoretical foundations, (10) bias position in the paper, (11) prior research goal, and (12) level of analysis (Kroenung and Eckhardt, 2011; Yang and Tate, 2012). These factors are of three different types.

The factors of the first type (year, journal, bias(es), theoretical foundations) were directly collected from the papers’ full text. The second type contains deductively derived factors. These factors are research method, bias category and research field. For the factor research method, we adopted the taxonomy developed by Palvia et al. (2007) that comprises 14 individual research methods. Its application in other contexts has shown that this taxonomy is complete and can also be applied in other IS research areas outside the scope of the journal Information & Management, for which it was originally developed (Avison et al., 2008). For the factor industry context, we relied on the North American Industry Classification System (NAICS, 2012) of the United States Census Bureau. NAICS is the successor of the Standard Industry Classification (SIC) System, which has been widely used in research. Specifically, we adopted the top level classification from NAICS that distinguishes 20 industry sectors.

For the factor bias category, we aggregated the categorizations suggested by Burow (2010), Kahneman et al. (2011) and Lovallo and Sibony (2010), as well as Haley and Stumpf (1989) and Browne and Parsons (2012). The common rationale behind these categorizations is to assign individual biases to root categories based on their influence on the decision-making process, as it is proposed by, for example, Welford’s (1968) model. However, despite the development of a broad stream of literature around heuristics and cognitive biases, to the best of our knowledge, to date, there
is no standardized, generally accepted and scientifically grounded framework for cognitive biases. Besides being not completely consistent and uniform the above mentioned categorizations are also not exhaustive: while in one categorization a bias category is contained, in another one, it is not (e.g. Lovallo and Sibony’s (2010) categorization does not contain the category “decision biases”). Taking into account the purpose of this study—presenting a comprehensive overview of research for cognitive biases in IS—we preferred to be rather inclusive than exclusive by integrating the proposed bias categories. For the factor bias category we thus employed eight categories: 1=perception biases; 2=pattern recognition biases; 3=memory biases; 4=decision biases; 5=action-orientated biases; 6=stability biases; 7=social biases and 8=interest biases.

Perception biases particularly affect the processing of new information that is received by an individual. A potential subsequent decision and the resulting behavior are flawed, when based on this biased information (e.g. framing; Tversky and Kahneman, 1981). Pattern recognition biases occur when, in the evaluation of alternative patterns of thinking, barely known information or unknown information is discarded in favour of familiar patterns of thinking or information that currently happen to be present in the mind (e.g. availability bias/availability cascade; Tversky and Kahneman, 1973). Memory biases affect the process of recalling information that refers to the past and thereby substantially diminish the quality of this information, which is later used for decision-making. (e.g. consistency bias/reference point dependency; McFarland and Ross, 1987). Decision biases occur directly during the actual process of decision-making and diminish the quality of actual as well as future decision outcomes (e.g. illusion of control; Langer, 1975). Action-orientated biases and stability biases are two distinct subgroups within the category of decision biases. Stability biases make individuals stick with established or familiar decisions, even though alternative information, arguments, or conditions exist that are objectively superior (e.g. status quo bias; Kahneman et al., 1991). Action-oriented biases lead to premature decisions made without considering actually relevant information or alternative courses of action (e.g. overconfidence bias; Keren, 1997). Social biases affect the perception or evaluation of alternatives and decisions and thus might occur at different stages of the decision-making process. Biases from this category arise from attitudes shaped by the individual’s relationship to other people (e.g. herd behavior; Scharfstein and Stein, 1990). Interest biases lead to suboptimal evaluations and/or decisions owing to an individual’s preferences, ideas, or sympathy for other people or arguments. These are also biases that might occur at different stages of the decision-making process. Resulting decisions can potentially have negative consequences for third parties (e.g. self-serving bias; Babcock et al., 1996).

The individual biases, which had been explored in the 84 identified IS papers were each assigned to a category based on the respective bias’ and the categories’ definitions². In this process, two researchers examined and discussed each definition until they agreed on in which category the respective cognitive bias is to be located (Barki et al., 1988). Subsequently, these results were discussed and validated by two experts from cognitive psychology.

The factor research field was examined based on seven categories: 1=research for business models of information systems; 2=software development; 3=application systems; 4=IS management; 5=IS usage; 6=economic impact of IS; 7=meta-research. These categories were theoretically derived from a consolidated review of existing categorizations of the IS research field. Thereby, we relied on Barki et al. (1988; 1993), Alavi and Carlson (1992), Claver et al. (2000), Vessey et al. (2002), Avison et al. (2008) and Dwivedi and Kuljis (2008).

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² A complete list of the bias definitions’ sources and the categories’ definitions can be obtained from the authors upon request.
Finally, factors of the third type have been developed inductively during the analysis of the articles, as recommended and described by Yang and Tate (2012, p.41). This approach resulted in the following five categories: measurement (1=interpretative measurement, e.g. qualitative/case study; 2=semi-objective measurement e.g. survey without objective baseline; 3=objective measurement, e.g. laboratory experiment, survey with objective base line), prior research goal (1=explanation of biases; 2=avoidance or targeted use of biases), bias position in paper (1=weak; 2=medium; 3=strong), bias impact (1=positive; 2=negative) and level of analysis (1 =individual; 2=group/collective).

To ensure objectivity and reliability in the coding process, we set up a codebook, including proof-texts for each value in the categories of types two and three. The content analysis was performed by two researchers (Krippendorff, 2004). To evaluate the content analysis’ interrater reliability, a random 20% sample of articles was double-coded. The resulting interrater reliability, measured by Krippendorff’s alpha, was 96 %, which is considered a high interrater reliability (Holsti, 1969). All 84 articles were categorized according to the described categorization scheme. The evaluation results are presented in the following section.

3 Results of the Scientometric Analysis

3.1 Cognitive biases in IS research over the past 20 years

Figure 1 shows a clear increase of interest in cognitive bias research in the IS discipline over the past 20 years, especially after 2008. It depicts the share of the identified articles, compared to the overall number of publications in the examined outlets for a given year.

![Figure 1. Publications on Cognitive Biases in IS between 1992 and 2012.](image)

Most of the 84 identified articles we extracted were published in the ICIS proceedings (18). 16 were published in DSS, 13 in ISR, 10 in MISQ, 9 in JMIS, 8 in IJEC, 4 in ECIS, 3 in ISJ, 2 in JAIS, and 1 in EJIS. We did not identify any publications on cognitive biases in JIT or JSIS.

3.2 Different types of cognitive biases in the IS discipline

Concerning the distribution of the individual cognitive biases, we found that the most commonly examined cognitive biases are framing (n=14) and anchoring (n=10). In addition, there are some moderately well-studied cognitive biases such as negativity bias (n=7), sunk cost bias (n=7), confirmation bias (n=5), and the halo effect (n=4). We also observed a considerable amount of cognitive biases investigated in only one article, such as the exponential forecast bias or the cultural bias. Finally, there are also some cognitive biases that have not yet been investigated in the IS
discipline but have been studied in other disciplines. Examples include the sunflower management bias (Boot et al., 2005), groupthink (Janis, 1972; Aldag and Fuller, 1993), or the planning fallacy (Buehler et al., 1994).

Table 1 shows the cognitive biases we identified in our scientometric analysis, including the frequency of occurrence and sample articles. The total number of identified biases is 120. This number is larger than the total number of relevant articles (n=84) because in some articles more than one cognitive bias were investigated.

<table>
<thead>
<tr>
<th>Category</th>
<th>Biases</th>
</tr>
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<tbody>
<tr>
<td>Perception biases (n=40)</td>
<td>framing (n=14, e.g. Allport and Kerler, 2003; Cheng and Wu, 2010); negativity bias (n=7, e.g. Yin et al., 2010; Wu et al., 2011); halo effect (n=4, e.g. Chong, 2004; Djamashi et al., 2010); selection bias (n=3, e.g. Aral et al., 2011; Ma and Kim, 2011); representativeness bias (n=2, Lim and Benbasat, 1997; Calikli et al., 2012); sequential bias (n=2, Piramuthu et al., 2012; Purnawirawan et al., 2013); priming effect (n=2, Stewart and Malaga, 2009; Dennis et al., 2013); recency effect (n=2, Pathak et al., 2010; Ghose et al., 2013); biased perception of partitioned prices (n=1, Frischmann et al., 2012); emotional bias (n=1, e.g. Turel et al., 2011); primacy effect (n=1, Lim et al., 2000); selective perception (n=1, e.g. Dennis et al., 2012).</td>
</tr>
<tr>
<td>Pattern recognition biases (n=11)</td>
<td>confirmation bias (n=5, e.g. Huang et al., 2012; Turel et al., 2011); availability bias (n=4, e.g. Lim and Benbasat, 1997); reasoning by analogy (n=1, Chen and Lee, 2003); disconfirmation bias (n=1, Rouse and Corbitt, 2007).</td>
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<tr>
<td>Memory biases (n=1)</td>
<td>reference point dependency (n=1, Vetter et al., 2011a)</td>
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<tr>
<td>Decision biases (n=24)</td>
<td>irrational escalation (n=4, e.g. Keil et al., 2000; Boonthanom, 2003); reactance (n=4, e.g. Murray and Häubl, 2011; Aljukhadar et al., 2012); illusion of control (n=3, e.g. Dudezert and Leidner, 2011; Vetter et al., 2011b); cognitive dissonance (n=3, e.g. Vetter et al., 2011a; Turel et al., 2011); mental accounting (n=2, Gupta and Kim, 2007; Kim and Gupta, 2009); mere exposure effect (n=2, Yang and Teo, 2008; Lowry et al., 2008); exponential forecast bias (n=1, Arnott and O’Donnell, 2008); ambiguity effect (n=1, Bhandari et al., 2008); zero-risk bias (n=1, Frischmann et al., 2012); input bias (n=1, Ramachandran and Gopal, 2010); base-rate fallacy (n=1, Roy and Lerch, 1996); omission bias (n=1, Hong et al., 2011).</td>
</tr>
<tr>
<td>Action-orientated biases (n=9)</td>
<td>overconfidence (n=6, e.g. Van der Vyver, 2004; Tan et al., 2012); optimism bias (n=3, e.g. Rhee et al., 2005; Nandedkar and Midha, 2009).</td>
</tr>
<tr>
<td>Stability Biases (n=24)</td>
<td>anchoring (n=10, e.g. Allen and Parsons, 2010; George et al., 2000); sunk cost bias (n=7, e.g. Vetter et al., 2010; Lee et al., 2012a); status quo bias (n=4, e.g. Gupta et al., 2007; Kim and Kankanahalli, 2009); loss aversion (n=2, Davis and Ganeshan, 2009; Yin et al., 2012); endowment effect (n=1, Rafaeli and Raban, 2003).</td>
</tr>
<tr>
<td>Social biases (n=9)</td>
<td>herding (n=4, e.g. Duan et al., 2009; Wang and Greiner, 2010); stereotype (n=2, Clayton et al., 2012; Quesenberry and Trauth, 2012); value bias (n=1, Hosack, 2007); attribution error (n=1, Rouse and Corbitt, 2007); cultural bias (n=1, Burtch et al., 2012).</td>
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<tr>
<td>Interest biases (n=2)</td>
<td>after-purchase rationalization (n=1, Turel et al., 2011); self-justification (n=1, Keil et al., 1994).</td>
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</table>

Table 1. Categorization of Biases, n=120.
3.3 Cognitive biases and their context

As noted above, to create a more comprehensive picture of the state of research on cognitive biases in the IS discipline, it is important to determine not only which types of cognitive biases have already been studied, but also in which research fields and in which industry contexts they have been investigated. Figure 2 therefore depicts a matrix comprised of bias categories and IS research fields. Each cell in this matrix holds the number of biases examined in a certain category and in a particular IS research field. Figure 2 shows that research on cognitive bases is not equally distributed over the research fields. There are certain combinations, such as IS usage and perception biases (n=27), IS usage and decision biases (n=16), or IS usage and stability biases (n=14) that have been investigated repeatedly so far. On the other hand, there are closely related combinations such as IS usage and memory biases that have not been examined in IS research at all (see footnote 3, p.9). These research gaps will be addressed in more detail in section 4.2 in which we provide concrete avenues for future research as well.

![Figure 2. Bias Category – IS Research Field Results Matrix.](image)

Furthermore, we observed that the largest share of biases in our sample was explored outside any specific industry context (n=41). In those cases in which cognitive biases were examined in a particular context, retail trade (n=37) and information (e.g. software, publishing, broadcasting, telecommunications) (n=15) were the most researched industries. In contrast, the sectors arts and entertainment (n=2), real estate (n=1), manufacturing (n=1) and health care and social assistance (n=1) have to date received little attention. However, there is also a set of industry sectors in which we found no research at all on cognitive biases. Concerning combinations between certain bias categories and industry contexts, we found the same phenomenon as with the combinations between bias categories and industry fields, i.e. areas with extensive research (retail trade and perception biases, n=20) and others with none (retail trade and memory biases, n = 0).

3.4 Theoretical foundations and methodology in cognitive bias research

Most of the 84 articles we examined stated that they used prospect theory (n=13), cognitive bias theory (n=9) and theory of planned behavior (n=7) to develop a research model or to explain their empirical results. Other theories that were reported were behavioral decision theory (n=7), status quo bias theory (n=4), cognitive dissonance theory (n=4) and bounded rationality (n=3). Three articles
claimed to be based on *behavioral economics theories* without specifying which theory in particular they considered. 13 articles did not refer to any theory to explain cognitive biases.

Concerning the research method of the studies on cognitive biases in IS, most utilized a *laboratory experiment* (26) or a *field experiment* (9). 18 studies were based on *survey data*, 15 on *secondary data analysis*. Ten articles reportedly used a *multi-method* approach for conducting their study. Only a few authors made use of a *mathematical model, case study or interviews* as a research method.

Closely related to the research method is the approach used for measuring the cognitive bias of interest. To analyse this, we inductively developed three measurement categories based on the analysis of the research method of each paper: qualitative, quantitative argumentative, and quantitative objective. Most of the publications (n=41) apply what we label an *objective measurement* (e.g. Lowry et al., 2008). We consider a bias measurement to be objective, when elicited or observed decision making is quantified and then benchmarked against an objective, rational baseline or a control group in the case of experiments (e.g. Kahneman and Tversky, 1979). The authors of 29 papers employed a *quantitative argumentative* approach to research the bias(es) of interest. In these cases, survey or observational data are analysed with e.g. regression or structural equation modelling. The effects found, are attributed to certain biases argumentatively (e.g. Gupta and Kim, 2007). Only 6 of the papers rely on a *qualitative* approach to explore the existence and the effects of cognitive biases. In these cases, observed correlations are attributed to certain biases argumentatively (e.g. Ramachandran and Gopal, 2010). Examples for applied research methods here are interviews and case studies. Eight articles did not refer to any bias measurement at all.

### 3.5 Bias position in paper, prior research goal and level of analysis

Moreover, we found that in the vast majority of cases, cognitive biases took a strong (n=58) or medium (n=17) position in the article. This means that cognitive biases were at the center of the research study and not just examined as an ancillary phenomenon. Furthermore, most papers’ primary research goal was the explanation of the cognitive bias phenomenon (n=64). Only 20 articles attempted to develop a specific way to avoid the occurrence of the respective cognitive bias (“de-biasing strategies”) or its targeted application. Finally, we investigated whether the research on cognitive biases was conducted at the individual or the group level of analysis. The results show that almost all research was conducted at the individual level (n=72). Only 12 articles examined cognitive biases at the group level.3

### 4 Discussion and Research Opportunities

#### 4.1 Key findings

With our scientometric analysis, we have provided a comprehensive overview of research on cognitive biases in IS (see RQ1). Based on this analysis, we will subsequently summarize our findings, provide a more in-depth discussion of the state-of-the-art in cognitive bias research in IS and derive possible avenues for future research.

The findings from our scientometric analysis raise several key points. First, we found a distinct upward tendency in IS research on cognitive biases in the past 20 years. Additionally, we observed

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3 A complete table including matched research fields, bias categories, bias position in paper, prior research goal and level of analysis for each individual article can be obtained from the authors upon request.
that in the vast majority of the examined articles, cognitive biases took center stage rather than being pushed to the sidelines. This rapid growth of publications and the focus on cognitive biases as a central research object can be interpreted as increasing acceptance of cognitive biases as a salient and legitimate research area in the IS discipline. Nonetheless, it was most articles’ research goal to provide an explanation of the cognitive bias phenomenon rather than to develop ways and strategies for its avoidance or targeted use. This might indicate that the research on cognitive biases in the IS field is still in its infancy, as we suggest that explaining a phenomenon in a defined research field is often the initial step, and advancing it—the subsequent one.

In addition, and as expected, we found that the vast majority of papers focused on the individual level of analysis. This, again, supports our suggestion that bias research in IS is still in its infancy, since biases at the individual decision-making level were also the ones that were first explored in early cognitive bias research (e.g. Tversky and Kahneman, 1973) before more sophisticated, group-related phenomena (e.g. herd behavior, Scharfstein and Stein, 1990) were explored. Moreover, our finding of research conducted predominantly at the individual level was reflected in the fact that e-commerce was one of the most prominent research settings in the papers we identified in our scientometric analysis. In e-commerce, it is common to investigate decision-making at the individual level (Smith and Brynjolfsson, 2001; Corbitt et al., 2003; Cowart and Goldsmith, 2007). However, since the influence of social networks is increasing (Wilcox and Stephen, 2013) and their use often leads to decision-making at the group level (Kempe et al., 2003; Kim and Srivastava, 2007), future research should pay more attention to the influence of cognitive biases on group decisions. It might be particularly interesting to explore the influence of social biases such as value bias or cultural bias (see Table 1) in group-decision-making processes (e.g. in online communities). In addition, it would be reasonable to conduct studies investigating whether results on cognitive biases gained in a particular individual decision-making context could readily be transferred to a group decision context.

Regarding the theoretical foundations to which the examined studies referred, we observed that most authors provided a reasonable basis for their investigation of the respective cognitive bias (e.g. prospect theory). However, we also identified a considerable amount of articles, where this was not the case and no or an insufficient theoretical basis was provided. We therefore advocate the use of a solid theoretical basis and its explicit argumentation and discussion in future IS studies on cognitive biases.

Concerning the employed research methods and bias measurement, our scientometric analysis identified that there are 41 articles using quantitative and objective bias measurement methods. Since cognitive biases are latent phenomena and cannot be observed directly, for a definite proof, it would be required to benchmark assumed biased decisions against an objective baseline (Kahneman and Tversky, 1979). However, this does not mean that using qualitative or quantitative, argumentative methods such as interviews or secondary data analysis (e.g. regression) are inappropriate at all. The method of choice should always depend on the research questions of interest. Nonetheless, we recommend being aware of the methodological peculiarities required by bias-related research when selecting research methods for future studies.

4.2 Avenues for future research

For the remainder of our paper, we return to the individual IS research fields and discuss existing and potential bias-related research in order to exemplarily present opportunities for future research (see RQ2).

In the research field IS usage, we could identify three large clusters: (1) e-commerce (B2C), (2) technology adoption and post adoption research, and (3) decision support system and recommender system use. Combined, these three clusters alone make up half of the 84 bias-related articles we identified in our analysis. Therefore, we dedicate a more extensive discussion to this research field.
The dominant themes in the e-commerce cluster (23 articles) are online reviews (e.g. Yin et al., 2012), product choice (e.g. Davis and Ganesan, 2009), pricing (e.g. Goh and Bockstedt, 2013), trust in online shopping (e.g. Lowry et al., 2008) and customer retention (e.g. Park et al., 2010). With regard to biases, the most widely examined category in IS usage is perception biases, and here, the most prominent single bias is framing. As an extension of the existing investigation of framing, we recommend examining the effect of different framing operationalization options. It could not be just the wording, that is framed, but also other web-design characteristics such as size, color, presentation mode (e.g. dynamic vs. static), saliency of website objects etc. While there is already a considerable amount of research on these characteristics, such articles are most often not grounded in theoretical foundations that are related to cognitive biases or non-rational decision-making at all (Li et al., 2012; Lee et al., 2012b). Recognizing cognitive biases in such studies may, however, provide substantial new insights for IS research in general and human-computer interaction research in particular.

The second cluster (10 articles) in the research field IS usage contains articles that discuss biases in the context of technology adoption (e.g. sunk cost bias, Polites and Karahanna, 2012) and post- adoption theory (e.g. status quo bias, Hong et al., 2011). Although adoption is one of the more mature areas in IS, and there are widely acknowledged models such as UTAUT and UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012), it could be helpful to consider the role of cognitive biases more explicitly, given that in existing models, bias-related concepts such as “habit” (e.g. as reflected in biases such as the status quo bias) are already included (Venkatesh et al., 2012). This might not only contribute to better understand and explain IS users’ adoption behavior and thus advance existing adoption and post-adoption theories. It might also lead to a better prediction of possible nonrational adoption-decisions, resulting from the influence of cognitive biases. Research for software selection is another area where biases have so far received little attention (e.g. Benlian, 2011; Benlian and Hess, 2011).

The third cluster within IS usage (9 articles) includes issues of decision support system use (e.g. Kahai et al., 1998) and recommender system use (e.g. Pathak et al., 2010). Pathak et al. (2010) for example explore the recency effect and propose that future research could adopt different types of recommendation approaches, such as content-based or hybrids of content-based and collaborative filtering mechanisms. We additionally recommend exploring this perception bias (see Table 1) in combination with the framing effect. This might allow the uncovering of the conditions of recommendation-framing under which the recency effect is most influential or, in turn, which might deflake it. Such additions could advance the research for recommender system use where biases have often not been considered explicitly (e.g. Benlian et al., 2012a). In summary, we could observe that in the field of IS usage there already exist important contributions focusing on the phenomenon of nonrational decision-making. Nonetheless, we could also identify a research gap (see Figure 2). The bias category memory biases is yet not examined at all in IS usage. However, it could be particularly interesting to see how “old” decisions can bias “new” ones, or, in other words, how the reference point dependency bias (McFarland and Ross, 1987) influences user behavior.

Furthermore, a closer look at the research field IS management shows that, similar to IS usage, there are three areas that have so far been addressed more intensely with regard to cognitive biases: these are IT outsourcing (Ramachandran and Gopal, 2010; Vetter et al., 2010; Vetter et al., 2011a), IS project escalation (Keil et al., 1994; Boonthanom, 2003), and IS security (Kannan et al., 2007; Anderson and Agarwal, 2010). In this context, IS security might be an area that is particularly worthwhile further exploring, since companies are increasingly shifting their business processes to IS and might thus put their entire business at stake through insufficient or flawed IS security (Campbell et al., 2003; Cavusoglu et al., 2004). Future research concerning the development of ways for avoiding biases in decisions regarding corporate IS security might thus be beneficial. In addition, we could not find any bias-related research in the areas of software evaluation, knowledge management, and selection decisions. These research gaps in IS management also hold potential for future research studies. In the area of selection decisions for example, biases from the category decision biases, e.g.
illusion of control (Langer, 1975), the choice supportive bias (Brehm, 1956) or neglect of probability (Sunstein, 2002) could be specifically interesting to explore.

In the research field software development, the identified articles deal with different aspects of the software development cycle (Laudon and Laudon, 2013). One article deals with requirements elicitation (Jayanth et al., 2011); two articles deal with the design of software (Rafaeli and Raban, 2003; Arnott, 2006) and one article addresses quality management (Calikli et al., 2012). In addition to that, two articles deal with the general management of software development projects (Keil et al., 2000; Lee et al., 2012a). However, among the identified articles, there is no research that deals with cognitive biases at the actual implementation stage. We argue, however, that this is a worthwhile area to explore cognitive biases, because even in a structured software development process, a considerable amount of decision-making remains in the responsibility of the individual developer.

With regard to cognitive bias research, we found the field of application systems to be dominated by articles that discuss the functionality and system architecture of decision support systems (e.g. George et al., 2000). While decision support system functionality is an obvious object of investigation in this research field, a closer investigation of other corporate application systems as well as consumer application systems may offer ample potential for further bias related research. For example, the functionality and performance of customer relationship management (CRM) systems might benefit from an explicit consideration of herding effects among customers. At the consumer side of application systems, operators of social networks might be able to increase their members’ satisfaction by considering social biases (see Table 1) in the architecture and functionality of their services.

Because research on business models of ICT firms is a rather new field in IS (Veit et al., 2014), a lack of findings in our literature search is consistent with the overall few publications on this topic. Nonetheless, we suggest that it is also worthwhile to explore cognitive biases in this particular research field. For example, the process of creating a business model for an ICT venture itself might be prone to biases. The identification of market potential, the development of a revenue model, or the actual implementation of an ICT business model is often performed by an individual or few decision-makers, i.e. entrepreneurs. Examining the appropriateness of transferring Kahneman et al.’s (2011) checklist for identifying potential biases in impending decisions to the ICT entrepreneurship context might be an interesting question that could be examined in future research studies.

Additionally, in the field economic impact of IS, we did not discover any publications concerning research on cognitive biases (see Figure 2). One explanation of this finding might be that a large portion of research in this field does not rely on cognitive approaches and individual decision-making (e.g. Kraemer and Dedrick, 1998). Nonetheless, we argue that it might be worthwhile to also consider biases in this field. In particular, the group of social biases, such as herd behavior, might affect the economic impact of IS through the virulence observed in online social communities (Chen et al., 2010).

Finally, the lack of sufficient meta research related to cognitive biases in IS is the primary motivation for our scientometric analysis. The results of our study confirm the existence of this research gap and provide additional evidence for the relevance and necessity of conducting a literature review on cognitive biases in IS in order to derive implications for IS specific research topics.

In summary, we can conclude that in cognitive bias related IS research, there are some leading fields such as IS usage and IS management and also some leading contexts, such as retail trade and information, but also others that are less or not examined at all (e.g., business models of ICT-firms or economic impact of IS). Future research can delve deeper into the individual IS research fields, discuss its goals and the types of cognitive biases examined in this field, reveal their implications for the field, and dispute the possible implications of non-investigated biases or elaborate on how examining other types of biases can contribute to this field. The abovementioned opportunities for future research
studies, as well as our results matrix (see Figure 2) could serve here as a meaningful point of departure.

5 Limitations and Conclusion

As with any study, there are some limitations that we discuss below. First, in our scientometric analysis, we focused on the top-rated publications in IS research and thus neglected other IS journals or conferences that may include articles on cognitive biases (e.g. Benlian et al., 2012b). Although we consider this focus an acceptable limitation, we nonetheless suggest that future literature reviews may include a more extensive set of IS journals and conference proceedings to validate our findings.

Second, for the factor bias category in our scientometric analysis we could not find any uniform and complete existing typology. We therefore integrated existing typologies, in order to achieve a preferably exhaustive bias categorization. We, however, are aware of the shortcomings of the applied approach and therefore recommend future studies on cognitive biases to further address the categorization of biases, focusing on and working toward the development and verification of a unified typology of cognitive biases.

Third, some categories of the categorization scheme used for the data analysis (e.g. bias position in paper and bias impact) are to some extent interpretative. Given the high interrater reliability of our coding process (96%) and the ongoing validations through experts, however, we are confident that our results are as objective as possible. Nevertheless, future literature reviews on cognitive biases may additionally validate the categories employed in our analysis.

Finally, for reasons of space, we could only briefly and exemplarily discuss potential topics for bias-related future research studies. The results of our scientometric analysis nevertheless provide an objective basis for a prompt identification of which cognitive biases have already been covered in previous IS research and which ones have not (possible research gaps). We are therefore confident that this scientometric analysis can be a useful starting point for IS researchers interested in cognitive biases. However, while figure 2 seems a promising tool for identifying research gaps in cognitive bias research, we also advise that the results from this matrix are to be interpreted with caution. Considering the identified research gaps in the individual IS fields, we don’t claim, that cognitive bias research should be equivalently distributed across all these fields. We thus also don’t recommend investigating all cognitive biases in all industries, for it is for example possible that the types of biases more likely to occur in “application systems” or “economic impacts of IS” categories are different from those in “IS usage” research. In other words, not every research gap in this matrix is per se a research area which should be explored. On the other hand, intensely researched bias categories and research fields must not be mistaken for over-researched areas where no further investigations are required. Hence, if the investigation of a certain combination of bias category, research field and industry context is desirable and should be pursued in future research, should still be evaluated case by case, also because the need for research in certain areas and the aforementioned meaningfulness of economic and societal contributions may shift over time.

In conclusion, this study’s main research contribution is to be seen in providing a comprehensive picture of the state of research on cognitive biases in the IS discipline. Such an overview enables finding links between existing research studies, identifying research gaps, providing directions and implications for future research and, in this way, contributing to cumulative knowledge-building. In summary, our literature review supports our initial claim, that insights from psychology, and in particular cognitive biases, can further enrich existing theories and models in IS, increasing their explanatory power. Ultimately, it is our hope that the findings of this scientometric analysis will encourage many IS researchers to further explore the exciting phenomenon of cognitive biases and thus will serve as a springboard for future research studies.
References

(Articles that were included in our scientometric analysis are marked with *)


