Overconfidence in IT Investment Decisions: Why Knowledge can be a Boon and Bane at the same Time

Completed Research Paper

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Abstract

Despite their strategic relevance in organizations, information technology (IT) investments still result in alarmingly high failure rates. As IT investments are such a delicate high-risk/high-reward matter, it is crucial for organizations to avoid flawed IT investment decision-making. Previous research in consumer and organizational decision-making shows that a decision’s accuracy is often influenced by decision-makers’ overconfidence and that the magnitude of overconfidence strongly depends on decision-makers’ certainty of their knowledge. Drawing on these strands of research, our findings from a field survey (N=166) show that IT managers’ decisions in IT outsourcing are indeed affected by overconfidence. However, an in-depth investigation of three types of knowledge, namely experienced, objective and subjective knowledge, reveals that different types of knowledge can have contrasting effects on overconfidence and thus on the quality of IT outsourcing decisions. Knowledge can be a boon and bane at the same time. Implications for research and practice are discussed.

Keywords: overconfidence, IT investment decisions, decision biases, knowledge types, IT outsourcing, miscalibration, better-than-average effect, illusion of control
Introduction

Since the late 1970s, organizations around the globe have made tremendous investments in information technology (IT). World IT spending now exceeds $3 trillion annually as companies around the world embrace IT (Gartner 2009). Yet, the relationship between IT investments and anticipated returns has perplexed researchers over the last decades because IT investment decisions, despite their strategic potential to increase productivity and firm performance (Sabherwa and King 1995), still show significantly higher failure rates in comparison to other investment decisions in companies (Yeo 2002). Around 23% of all IT projects still fail, and IT projects labeled as ‘challenged’ (i.e., suffering from budget overruns and/or program slips and offering lesser functionality than originally specified) often add up to more than 50% of all IT projects in organizations (Du et al. 2007; Yeo 2002).

Given these sobering statistics, it is of vital importance for organizations to make sound IT investment decisions that are not misled by undue risk-taking behavior of IT executives (Benaroch et al. 2007; Benaroch 2002). Research in organizational decision-making and behavioral science indeed shows that decision quality is strongly influenced by the behavior of individual decision-makers or decision groups. There is, for example, agreement in research literature that the adoption of IT outsourcing practices is a major management decision made by individuals rather than organizations. Empirical studies have indicated that final decisions regarding the sourcing of IT functions are mostly made by an organization’s highest-ranking IT executive (Apte et al. 1997) and that these decisions are often based on decision heuristics due to limitations in time, information and cognitive resources (Simon 1959). In this regard, overconfidence has been found to be one of the most robust heuristics (McKenzie et al. 2008) serving as an explanation for severe failures in decision-making, such as entrepreneurial failures or stock market bubbles (Glaser and Weber 2007). The influence of overconfidence on behavior has also been shown to vary across different personal characteristics of decision-makers. Among several different cognitive and motivational reasons for overconfidence (Keren 1997), different types of knowledge are consistently mentioned as a main impetus for overconfident behavior (Forbes 2005; McKenzie et al. 2008; Menkhoff et al. 2006). As studies in IS research also indicate that IT managers often have very different knowledge backgrounds, ranging from a strong technical focus to a rather general management focus (Enns et al. 2003; Bassellier et al. 2001), examining the impact of different knowledge types on overconfidence should clearly be of value for IT managers and researchers alike.

Drawing on decision-making and consumer research literature, this study investigates the role of three types of knowledge – experienced knowledge, objective knowledge and subjective knowledge (Brucks 1985) – in influencing overconfident behavior of IT decision-makers. To the best of our knowledge, no research has been conducted so far that has explicitly focused on how these different types of knowledge affect IT decision-makers’ overconfidence and thus the ability to make sound IT investment decisions. Examining this relationship, however, has a theoretical as well as practical relevance. On the one hand, there is no consensus in the academic literature regarding whether too much or too little knowledge leads to a reduction of overconfidence (Skala 2008). A more nuanced perspective would thus advance our understanding of the role of different kinds of knowledge in affecting overconfidence of IT decision-makers. On the other hand, understanding the link between knowledge and overconfident behavior is important for practice because “managers who fall prey to various heuristics and biases [such as overconfidence] while making decisions [...] are a major source of risk for good decisions” (Khan and Stylianou 2009, p. 64). To understand what types of knowledge are indicative of overconfidence would thus help practitioners to better manage overconfidence and its detrimental consequences (Russo and Schoemaker 1992). In our study, we address two main research questions:

(1) Do IT decision-makers suffer from overconfidence or not?
(2) How are different types of knowledge related to IT decision-makers’ level of overconfidence?

The remainder of the paper is organized as follows. We begin by introducing the conceptual foundations of this paper, including overconfidence and different types of knowledge. Then, we present our research model and develop our hypotheses on the relationship between the different knowledge types and IT decision-makers’ overconfidence. Further, we present the design and research methodology of the study and report our results. After discussing the findings, the paper highlights implications for both research and practice and points out promising areas for future research.
Conceptual Foundations

Overconfidence and Previous Studies in IS Research

The term ‘overconfidence’ has been widely used in psychology since the 1960s. Despite extensive research on overconfidence in subsequent decades that, for example, found that overconfidence is “perhaps the most robust finding in the psychology of judgment” (DeBondt and Thaler 1995), its origins and reasons for its existence have not been clearly and unambiguously defined (Skala 2008). Since the overconfidence phenomenon was first considered by other fields of research in the 1970’s, including economics and finance, the meaning of overconfidence has been stretched beyond its original definitions. Different streams of research in behavioral research evolved an array of operationalizations that fall under the common label of overconfidence. In recent overconfidence research studies, three phenomena have been used to tap into overconfidence: miscalibration, better-than-average effect and illusion of control (Deaves et al. 2010; Moore and Healy 2008).

In psychology, calibration is usually studied on the basis of general knowledge questions (e.g., comparisons of population sizes of different cities or their geographical position) generated by researchers. Study participants answer sets of questions, and after each particular item (or after a set of questions or at the end of the whole task), they have to assess the probability that the given answer (or the whole set) was correct. Appropriate calibration takes place “if over the long run, for all propositions assigned a given probability, the proportion that is true is equal to the probability assigned” (Koriat et al. 1980, p. 109). Putting it simply, a well-calibrated judge is able to correctly assess the amount of mistakes he or she makes. Conversely, miscalibration refers to the difference between the accuracy rate and the probability assigned that a given answer is correct. The better-than-average effect usually refers to a cognitive bias that, in general, people tend to have an unrealistically positive view of themselves (Kruger and Dunning 1999). This causes people to overestimate their positive qualities and abilities and to underestimate their negative qualities relative to others (Dunning et al. 1989). Finally, illusion of control is the tendency of people to overestimate their ability to control events, even in situations governed purely by chance (Thompson 1999). Taken together, all three indicators reflect an individual’s overestimation of their own knowledge, which can have a serious impact on organizations, causing problems, such as stock market bubbles, as well as entrepreneurial and project failure (Glaser and Weber 2007).

Although most research studies in the past have focused on only one of the three indicators to capture overconfident behavior, more recent studies have advocated embracing all of them “[...] to keep these distinctions in mind for a more thorough understanding of underlying psychological processes and findings that directly influence the agents’ behaviour” (Skala 2008, p. 38). Hence, in keeping with more recent overconfidence research, our paper is based on the following definition, which includes all three indicators of overconfidence: Overconfidence is any behavior based on systematically incorrect assessments of one’s knowledge and skills as well as the actual ability to control future events.

In previous IS research, little attention has been paid to the investigation of overconfidence. Only a few studies have focused on overconfidence in IT decisions in general, as well as in more specialized domains like IT outsourcing. Der Vyver (2004), for example, found that IT managers show better accuracy in judgments and a better calibration than do accounting and marketing managers. Jamieson and Hyland (2006) found considerable empirical evidence of bias in IT investment evaluations in organizations, with both positive and negative impacts on decision outcomes. Rouse and Corbitt (2007) found non-rational effects such as overconfidence to be one reason for the phenomenon that managers outsource IT, although there is often no reliable and valid evidence for the outsourcing’s benefits. McKenzie et al. (2008) showed that IT experts and novices are similarly overconfident, with no significant differences between them. Based on a study of managerial biases in IT decision-making, Khan and Kumar (2009, p. 6) concluded that “at the project selection stage, overconfidence in IT managers may lead to overestimation of their knowledge”.

Overall, while to date a few studies have been dedicated to overconfidence in IT decision-making, to the best of our knowledge, no previous studies have empirically investigated what kinds of IT decision-makers’ knowledge types affect overconfident behavior (Khan and Kumar 2009). Examining the
relationship between knowledge types and overconfidence would, however, provide an advanced understanding of important antecedents of overconfidence in IT decision-making.

**Knowledge Types**

Russo and Schoemaker (1992) indeed claim that having accurate knowledge is essential for making good decisions and it has been demonstrated empirically that knowledge affects information search, information processing and decision-making (Brucks 1985; Carlson et al. 2009). In overconfidence literature, knowledge has also been identified as a main influencing factor for overconfidence (McKenzie et al. 2008; Zacharakis and Shepherd 1999). Drawing on previous consumer and decision-making research, knowledge can be divided into three main types of knowledge, namely experienced knowledge (EK), objective knowledge (OK) and subjective knowledge (SK) (Brucks 1985; Carlson et al. 2009).

EK, which has been studied in different strands of literature (Brucks 1985; Dodd et al. 2005; Raju et al. 1995), is generally considered a summation of a subject’s past product or domain-related experience, including knowledge about a product or domain, participation in a domain or use/ownership of a product (Alba and Hutchinson 1987; Dodd et al. 2005). Adapted to the IT context of our study, we define EK as a subject’s working (i.e., professional), IT-related (e.g., experience in the IT department) or domain-specific (e.g., IT outsourcing) experience that the subject has accrued in the past. OK denotes the actual content and organization of knowledge that is held in memory. In other words, OK refers to facts a person knows which can be assessed using objective tests of an individual’s knowledge (Raju et al. 1995). Transferred to the IT context, this type of knowledge refers to domain-specific knowledge about facts such as the market shares of main IT vendors or the growth rates of interesting new IT innovations (Russo and Schoemaker 1992). SK is the perceived level of a subject’s knowledge and has typically been measured by subjects’ self-reports of their knowledge of a product or a specific domain (e.g., Brucks 1985; Carlson et al. 2009). Hence, SK “[…] reflects what we think we know […]” (Carlson et al. 2009, p. 864) rather than an objective measurement of our knowledge. Transferred to the IT context, SK can be defined as subjects’ self-assessments of their knowledge in comparison to their peers (i.e., other IT managers).

**Hypothesis Development**

To illustrate our hypotheses on the influence of the three types of knowledge on IT decision-makers’ overconfidence, we propose the research model shown in Figure 1.

![Figure 1. Research Model](image_url)

Drawing on consumer and organizational decision-making research literature, we examine the effects of three different types of knowledge on overconfidence to find out whether IT decision-makers are overconfident or not and which type of knowledge is positively or negatively related to overconfidence in IT investment decisions. The research model in Figure 1 suggests that the different knowledge types do not affect overconfidence in the same way. Rather, it shows that we assume that experienced knowledge and subjective knowledge are positively associated with overconfidence, whereas objective knowledge is
Overconfidence in IT Investment Decisions

negatively related to a decision-makers’ overconfidence. In the sections that follow, we further elaborate on how the three different knowledge types affect IT decision-makers’ overconfidence.

**Experienced Knowledge and Overconfidence**

Experienced knowledge is considered one of the most important variables in the research of non-rational effects (Phillips et al. 2004). Recent research on the influence of EK on overconfidence shows some evidence that more experienced individuals do not perform better in decision-making than less experienced individuals (Shepherd et al. 2003). This is mainly due to the fact that individuals with higher levels of EK overestimate the relevance of their past experience by transferring it to completely different situations (Finkelstein et al. 2008). However, very rarely are two situations entirely similar. Misleading experience as a contributory factor to overconfident decisions has been confirmed by several other studies. Van de Venter and Michayluk (2008), for example, tested the forecasting ability of financial planners in Australia. Based on a calibration study, the participants had to supply a high and a low estimate for the S&P/ASX200 index by the end of the year. The participants were asked to choose the numbers far enough apart to be 90% sure that the actual answer would fall somewhere in between the two estimates. Interestingly, the two researchers found a “[…] positive correlation between overconfidence and years’ experience” (van de Venter and Michayluk 2008, p. 554). Further, Deaves et al. (2010) revealed “[…] that market experience does not lead to better calibration […]” (Deaves et al. 2010, p. 411). There is, rather, a significant negative correlation that indicates that “[…] experienced and successful market forecasters become even more overconfident over time […]” (van de Venter and Michayluk 2008, p. 554). Given these consistent results in recent empirical research studies, we argue that experienced knowledge will have a positive effect on IT decision-makers’ level of overconfidence. Accordingly,

**H1: IT decision-makers’ experienced knowledge is positively related to their level of overconfidence.**

**Objective Knowledge and Overconfidence**

“Charles Darwin (1871) sagely noted over a century ago, ‘Ignorance more frequently begets confidence than does knowledge’” (Kruger and Dunning 1999, p. 1121). Taking Darwin’s statement as a guiding hypothesis, Kruger and Dunning (1999) investigated people’s self-knowledge of whether they are incompetent in certain domains. They argued that the skills that engender competence are often the same skills necessary to evaluate one’s own or another’s competence in a specific domain. Hence, “[…] the same knowledge that underlies the ability to produce correct judgments is also the knowledge that underlies the ability to recognize correct judgments. To lack the former is to be deficient in the latter” (Kruger and Dunning 1999, p. 1122). In their research studies, Kruger and Dunning (1999) found that people who are objectively unskilled also “[…] suffer a dual burden: Not only do these people reach erroneous conclusions and make unfortunate choices, but their incompetence robs them of the meta-cognitive ability to realize it” (Kruger and Dunning 1999, p. 1121). These unskilled people significantly overestimate their own performance by rating their performance as better than average, although their actual performance is worse than average (Ehrlinger et al. 2008). In addition, Kruger and Dunning (1999) observed that not only do objectively incompetent people suffer from a distorted self-assessment of performance, but their objectively competent counterparts do as well. “Although they perform competently, they fail to realize that their proficiency is not necessarily shared by their peers” (Kruger and Dunning 1999, p. 1131). Kruger and Dunning (1999) found for objectively competent people that they underestimated their own performance in comparison to the peer group, rating their performance as below average, although their actual performance was above average.

Overall, the patterns found in the studies by Kruger and Dunning have been replicated across a wide range of subjects in a wide range of tasks of knowledge and skills (Ehrlinger and Dunning 2003). For example, people incorrectly perceive how well they have actually conveyed their feelings, doctors inaccurately estimate their level of knowledge of illnesses, and nurses erroneously evaluate their life support skills (Hodges et al. 2001; Tracey et al. 1997; Marteau et al. 1989; Riggio et al. 1985). People are also incorrect in their confidence estimates of the accuracy of their actions, such as their judgments of whether someone is lying (DePaulo et al. 1997) and their eyewitness identifications in a lineup (Sporer et al. 1995). This inability to accurately estimate one’s own performance becomes even more pronounced in situations of excessive cognitive load, as is most often the case when making high-stake decisions in
organizations (Roch et al. 2000). Based on this previous empirical evidence, we argue that IT managers also suffer from this pattern of incorrect self-assessment of performance in which objective knowledge is negatively associated with overconfidence. Hence, we derive

**H2:** IT decision-makers' objective knowledge is negatively related to their level of overconfidence.

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### Subjective Knowledge and Overconfidence

In contrast to objectively measurable knowledge metrics, subjective knowledge refers to people’s self-assessment of their own knowledge. This kind of knowledge has previously been associated with overconfidence, “[...] defined as an expectancy of a personal success probability inappropriately higher than the objective probability would warrant. It [can be] predicted that factors from skill situations [...] introduced into chance situations would cause [participants] to feel inappropriately confident.” (Langer 1975, p. 312). In other words, as psychological research demonstrates, people tend to believe they are able to influence events that in fact are governed mainly, or purely, by chance (Taylor and Brown 1988). This so-called ‘illusion of control’ thus refers to an overestimation of a subject’s ability to cope with and predict future events (Simon et al. 1999). An extreme example of this illusion would be an insistence on throwing dice personally, in the belief that this would lead to a more favorable result. Moreover, if people expect certain outcomes and these outcomes do occur, the participants are prone to assign the outcome to their skill rather than luck and thus re-affirm their belief in control over a situation where the only factor is probability (Langer 1975). Managers who suffer from this specific kind of overconfidence are dangerous to firms as they tend to generate overoptimistic performance estimates and, therefore, make excessively risky decisions (Barnes 1984). Illusion of control has been found in a variation of experiments on chance-driven tasks, including the participation of a confident or a nervous competitor, choosing lottery tickets or being assigned one, engaging in familiar or unfamiliar lotteries or chance games and making one’s own guesses or guessing through a proxy (Langer 1975). In all these situations, participants have been found to express excessive confidence in their control over outcomes of chance-driven tasks. A meta-analysis of Presson and Benassi (1996) also documents the prevalence of illusion-of-control effects across a wide range of studies and experimental variations. Previous research on the effects of subjective knowledge has shown that people with a high degree of subjective knowledge often do not want to involve or consult others in their own decision-making. Rather, they base their decisions on their self-assessed knowledge and, as a consequence, suffer from high illusion of control (Gino et al. 2011; Mattila and Wirtz 2002). In line with previous studies examining people’s illusion of control in decision-making, we thus argue that IT decision-makers who overestimate their own subjective knowledge also suffer from overconfidence, as indicated by high illusion of control. As such, we hypothesize that

**H3:** IT decision-makers’ subjective knowledge is positively related to their level of overconfidence.

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### Research Methods

#### Research Context, Procedures and Descriptives

We decided to base our research study on a specific IT investment decision that has gained continued popularity in recent years, namely IT outsourcing (ITO). ITO, the transferring of all or part of a company’s IT functions to an outside party, plays a major role in the strategic arsenal of today’s organizations (Benamati and Rajkumar 2002; Gorla and Mei Bik 2010). The ITO market accounts for 67% of all global outsourcing deals; the outsourcing industry grows rapidly, and firms across all industries and sizes outsource or consider ITO as an alternative to their internal IT functions (Benamati and Rajkumar 2002). Due to our focus on IT (i.e., ITO) decisions, only professionals working in the IT department of a company were addressed in our study. These professionals should have sufficient decision responsibility in their respective domain and, thus, should predominantly derive from middle and upper IT management. Based on a representative random sample extracted from the Hoppenstedt firm database, which is one of the largest commercial business data providers in Germany and contains over 300,000 company profiles, 400 IT managers were invited to an online survey. As incentives, we guaranteed response anonymity and also offered a free management report presenting the main results of our study. Out of 181 total
respondents, 15 had to be eliminated due to missing or inconsistent data, resulting in a net sample size of 166 (see further descriptive statistics on the survey respondents in Table 1).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Responses (in %)</th>
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<tbody>
<tr>
<td>Age (years)</td>
<td>18-24: 2.4  25-39: 27.7  40-54: 54.2  55-69: 15.1  &gt;70: .6</td>
</tr>
<tr>
<td>Gender</td>
<td>Male: 98.8  Female: 1.2</td>
</tr>
<tr>
<td>Hierarchy Level</td>
<td>Lower Mgmt.: 6.6  Middle Mgmt.: 66.9  Upper Mgmt.: 26.5</td>
</tr>
<tr>
<td>Professional Experience (years)</td>
<td>&lt;10: 10.8  10-20: 36.2  21-30: 34.9  31-40: 14.5  &gt;40: 3.6</td>
</tr>
<tr>
<td>Experience in IT Departments (years)</td>
<td>&lt;10: 22.3  10-20: 48.2  21-30: 23.5  31-40: 5.4  &gt;40: 3.0</td>
</tr>
<tr>
<td>ITO Experience (Decisions involved in)</td>
<td>&lt;4: 55.4  4-10: 33.2  11-20: 8.4  &gt;20: 3.0</td>
</tr>
</tbody>
</table>

Four weeks after the first email, we sent out a reminder email to all who had not yet answered. Non-response bias was assessed by verifying that responses received before and after the reminder email were not significantly different and by verifying that early (first 50) and late (last 50) respondents were not significantly different (Armstrong and Overton 1977). We compared the two samples based on their socio-demographics and responses to principal constructs. T-tests showed no significant differences (p>0.05), indicating that non-response bias was not a pervasive threat.

In quantitative mono-method research especially, common method variance (CMV) is a possible hazard, which we tried to address by following some suggestions from Sharma et al. (2009). For example, we used a number of different approaches (e.g., a calibration study and Likert scales) to capture both behavioral and self-reported measures for our independent and dependent variables. Moreover, we used items that measured factual and verifiable behaviors to keep items as concrete as possible. Finally, we guaranteed response anonymity as a procedural remedy to attempt to reduce method bias.

Measurement of Constructs

Drawing on previous studies in overconfidence and consumer research, we used miscalibration, the better-than-average effect and illusion of control to tap into overconfidence (Deaves et al. 2010; Moore and Healy 2008) and experienced, objective and subjective knowledge (Brucks 1985; Carlson et al. 2009) to capture the different knowledge types investigated in this study (see Tables 1 to 4 in the Appendix that includes the questions of the online survey).

Measurements of Overconfidence

Miscalibration is probably the most established operationalization of overconfidence and is usually measured within a so-called calibration study. During those studies, participants are asked a number of knowledge questions and about a single, numerical best estimate within each question (e.g., how many people live in the USA?). The participant then has to provide an interval corresponding to a given level of confidence, e.g., stating a high and a low estimate such that there is a X% chance that the correct answer falls somewhere within these limits (Klayman et al. 1999). The accuracy of such estimates is usually measured in terms of a hit rate that refers to how often the intervals provided by subjects contain the true value (McKenzie et al. 2008). Hit rates are often compared to the degree of confidence reported in the intervals. Van de Venter and Michayluk (2008) show, for example, that miscalibration can range from very high (hit rate=22% within a 90% confidence interval) to relatively low (hit rate =80% within a 95% confidence interval). Calibration studies are not usually seen as a quiz that is conducted to figure out what the participants do or do not know. They are rather conducted to measure how well participants are aware of what they do not know exactly.

Our study’s survey also included calibration tasks as a way of measuring overconfidence, asking the respondents to answer five knowledge questions. Based on the results of former studies, five questions is a sufficient number to get a reliable classification of participants based on their degree of miscalibration (Glaser and Weber 2007; Russo and Schoemaker 1992). Each question had one correct numerical answer. For each question, respondents had to provide a low and a high estimate that they were 90% certain to
capture the correct answer. Consistent with past research (McKenzie et al. 2008), the respondents were asked about domain-specific knowledge concerning ITO (e.g., What percentage of a firm’s total IT budget is expended on IT outsourcing?, or What percentage of German firms outsource their data centers?). The questions were extracted from two current surveys on the European ITO market conducted by Orange Business Services (Orange Business Services 2009) and PricewaterhouseCoopers (Messerschmidt et al. 2008). Based on the five knowledge questions, we computed the hit rate for each participant. We also calculated two other measures that are important for the interpretation of the hit rate, providing insights into why hit rates are relatively high or low. First, we subtracted the low estimate from the high estimate for each question and participant and averaged the interval sizes across the questions. This gave us an average interval size (or width) for each participant depicting the subject’s level of uncertainty. Second, the so-called interval error, i.e., the absolute value of the difference between the correct answer (i.e., the true value) and the midpoint of the interval, was calculated for each question and participant and also averaged across the questions. This absolute value should gauge subjects’ objective knowledge, as the interval error shows how well a participant can estimate the correct answer independently of the hit rate (Yaniv and Foster 1997). To avoid confounding effects from revealing the correct answers to the knowledge questions, the correct answers were presented to the participants only after they had submitted the survey.

A better-than-average effect occurs when people believe that they perform better than others in a certain peer group. According to Kruger et al. (1999), the better-than-average effect is thus usually measured by comparing people’s self-assessment of performance (relative to others) to their actual performance. Based on the operationalization of Kruger et al. (1999), we operationalized the better-than-average effect in a similar way. We asked the participants after answering the knowledge questions to guess how they performed relative to other participants by indicating the percentage of their peers (i.e., other IT decision-makers) that they think they have outperformed in the calibration study in terms of participants’ interval error. This value was then compared to the participants’ actual performance (i.e., actual interval error) derived from the calibration study. To arrive at an analysis similar to Kruger and Dunning’s analyses, we normalized the actual performance (i.e., the interval error) on 100% (Kruger and Dunning 1999).

To get a reliable measure for illusion of control, we adopted four items from previous overconfidence studies, with minor changes to the wording (Burger and Cooper 1979; Menkhoff et al. 2006). The respondents were asked to answer ITO-specific questions measuring their control position (e.g., Most of the news on ITO is not surprising to me; When a service provider does not meet the requirements as arranged, it is not surprising to me). To arrive at a single score for the control position of IT decision-makers, we averaged these items.

Measurement of Knowledge Types

In line with empirical studies on overconfidence and knowledge research (e.g., Forbes 2005; McKenzie et al. 2008; Menkhoff et al. 2006; van de Venter and Michayluk 2008), we measured experienced knowledge with several measures covering different aspects of decision-makers’ experience. Overall professional experience and working experience in IT departments were measured by the number of years of professional/IT experience. As a more domain-specific type of experienced knowledge, IT outsourcing experience was measured by the number of ITO decisions that IT managers have been involved with in their careers. Finally, we measured the hierarchy level of the participants in their respective organization by distinguishing between lower, middle and upper management (see also Table 1).

Objective knowledge “[...] has generally been assessed using objective tests of an individual’s extent of knowledge about a domain” (Raju et al. 1995, p. 154). As reported above and in line with previous calibration studies (e.g., Dodd et al. 2005; Raju et al. 1995), we used the actual interval errors from the calibration study as measures for OK indicating the precision of a participant’s answer. Subjective knowledge is generally assessed by subjects’ self-reports of their skills, performance, and past successes in a specific domain compared to their peers’ skills, performance and past successes (Brucks 1985; Raju et al. 1995). To cover these three aspects of subjective knowledge, we drew on three measures suggested in previous empirical studies capturing participants’ self-assessments related to their own skills, performance and past ITO successes in comparison to their peers (Larrick et al. 2007).
Results

**Experienced Knowledge and Overconfidence**

Hypothesis 1 predicted that there is a positive relation between experienced knowledge and overconfidence. Table 2 depicts the correlations between the different facets of EK (i.e., (1) hierarchy level, (2) professional experience, (3) experience in IT departments, and (4) ITO experience) and the hit rate we derived from our calibration study.

<table>
<thead>
<tr>
<th>Table 2. Correlations between the Experienced Knowledge and Hit rate</th>
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<tr>
<td>Hit Rate</td>
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<tr>
<td>1. Hierarchy Level</td>
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<tr>
<td>2. Professional Experience</td>
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<tr>
<td>3. Experience in IT Departments</td>
</tr>
<tr>
<td>4. ITO Experience</td>
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*p<0.05; **p<0.01

As this research study is still in an early stage of theorizing, we used a correlation analysis instead of more sophisticated statistical tests (e.g., regression analysis) to examine the relationship between experienced knowledge and overconfidence. Overall, although the correlation coefficients are rather low in absolute terms, the data indicate significant correlations between the hit rate and all EK variables. Hierarchy level \((r = .162; p < .05)\) and ITO experience \((r = .129; p < .05)\) show positive correlations with hit rate. Total professional experience \((r = -.265; p < .01)\) and experience in IT departments \((r = -.179; p < .01)\) are negatively (and significantly) related to hit rate, which shows that IT decision-makers with more work and IT experience are worse calibrated than inexperienced decision-makers. Only a higher hierarchical level and the involvement in ITO decisions lower the miscalibration by ITO decision makers. At first view, this result seems to be counterintuitive. Why should professional and IT experience make decision-making less calibrated? To find an answer to this question, one has to consider that the hit rate in calibration studies can be increased in two ways. McKenzie et al. (2008) argued that the participant either has more objective knowledge, and therefore produces smaller interval errors, or has less objective knowledge and chooses a larger interval size, which raises the chance of encircling the correct answer to get a hit. Consistent with Russo and Schoemaker (1992), decision-makers who do so know that they do not know the exact answer and therefore have a higher level of meta-knowledge, which refers to a person’s knowledge about the borders of his or her knowledge. As illustrated in Table 3, both effects can be shown in our study.

<table>
<thead>
<tr>
<th>Table 3. Correlations between the Levels of Experience, Error and Interval Size</th>
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<tbody>
<tr>
<td>Interval Error</td>
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<tr>
<td>Interval Size</td>
</tr>
<tr>
<td>1. Hierarchy Level</td>
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<tr>
<td>2. Professional Experience</td>
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<td>4. ITO Experience</td>
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</table>

*p<0.05; **p<0.01

IT managers that are on a higher hierarchical level \((r = -.144; p < .05)\) or have more experience in ITO decisions \((r = -.091; n.s.)\) show smaller interval errors in the calibration study. But they also broaden their
intervals. This is especially the case for participants with more ITO experience \((r = .147; p < .05)\). They are seemingly more aware of the complexity of the market. Due to this meta-knowledge, they are able to better assess their own objective knowledge. By contrast, participants with more professional experience \((r = .164; p < .05)\) or more experience in IT departments \((r = .168; p < .05)\) show larger interval errors. That means they have less objective knowledge. Furthermore, IT decision-makers with high professional experience in particular lower the interval size \((r = -.197; p < .01)\). Taken together, H1 can only be partially supported for some dimensions of experience. ITO experience and the level of hierarchy are negatively related to overconfidence, while professional experience and experience in IT departments are positively associated with overconfidence.

**Objective Knowledge and Overconfidence**

Are IT managers who do well in a certain task aware of their competence, and are bad ones aware of their incompetence? To answer this question we adopted a well elaborated test which was developed by Kruger and Dunning (1999). They posed the question, if people who do (bad) good in a certain task are aware of their (in-) competence? To answer this question, they assigned each participant a percentile rank based on their actual performance quartiles and plotted those ranks against the percentiles of their self-reported performance relative to peers (see also Ehrlinger et al. 2008 as an example for the used test). We adopted this procedure by using the interval error as actual performance indicator. On average, our participants put their performance in ITO decision making in the 58\textsuperscript{th} percentile, which exceeded the actual mean percentile (50, by definition) by eight percentage points (one-sample \(t(165) = 8.755, p < .0001\)). As Figure 2 shows, the participants in the bottom quartile grossly overestimated their performance relative to their peers. While their actual performance in the calibration study fell in the 34\textsuperscript{th} percentile, they (on average) put themselves in the 58\textsuperscript{th} percentile. These self-reported estimates were not only significantly higher than the ranking they actually achieved (paired \(t(40) = 9.008, p < .0001\)) but also significantly exceeded the actual mean percentile (one-sample \(t(40) = 4.128, p < .0001\)). As such, participants in the bottom quartile of the distribution rated themselves as better than average. Interestingly, participants in other quartiles did not overestimate their own performance. Participants in the second quartile, for example, assessed their own performance correctly. Those in the quartiles above the median significantly underestimated their performance relative to their peers (paired \(t_{3\text{rd} \text{quartile}}(41) = -6.786, p < .0001\) and \(t_{4\text{th} \text{quartile}}(40) = -14.632, p < .0001\)). Based on these findings, hypothesis 2 can be supported, as overconfidence (as indicated by the better-than-average effect) decreases with increasing objective knowledge.

**Figure 2. Self-Assessment of Performance in ITO as a Function of Actual Performance**
Subjective Knowledge and Overconfidence

Based on our third hypothesis, we proposed that people with higher subjective knowledge also show higher overconfidence in terms of illusion of control. Based on the self-assessment variables on skills, performance and success, we divided our sample into two groups for each variable. Group 0 consisted of participants who assessed their skills, performance or success as below-average or average, whereas group 1 consisted of participants who assessed themselves as above-average in the three given dimensions. Due to the non-normality of our data, we conducted nonparametric Mann-Whitney-U-tests. Table 4 shows that for all three dimensions, participants who rated themselves as above-average also showed significantly higher illusion of control in terms of their control position (p ≤ .01). These preliminary results support our hypothesis 3.

Table 4. Rank and Test Statistics for Illusion of Control

<table>
<thead>
<tr>
<th>Grouping Variable</th>
<th>N=166</th>
<th>Mean Ranks and Deltas</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Skills</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Below Average or Average (0)</td>
<td>97</td>
<td>75.08</td>
</tr>
<tr>
<td>Above Average (1)</td>
<td>69</td>
<td>95.33</td>
</tr>
<tr>
<td><strong>Mann-Whitney-U Asymp.Sig.(2-tailed)</strong></td>
<td></td>
<td>p = .007</td>
</tr>
<tr>
<td><strong>Performance</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Below Average or Average (0)</td>
<td>76</td>
<td>72.81</td>
</tr>
<tr>
<td>Above Average (1)</td>
<td>90</td>
<td>92.53</td>
</tr>
<tr>
<td><strong>Mann-Whitney-U Asymp.Sig.(2-tailed)</strong></td>
<td></td>
<td>p = .008</td>
</tr>
<tr>
<td><strong>Success</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Below Average or Average (0)</td>
<td>78</td>
<td>73.38</td>
</tr>
<tr>
<td>Above Average (1)</td>
<td>88</td>
<td>92.47</td>
</tr>
<tr>
<td><strong>Mann-Whitney-U Asymp.Sig.(2-tailed)</strong></td>
<td></td>
<td>p = .010</td>
</tr>
</tbody>
</table>

Taken together, the results of this preliminary study on the relations between knowledge types and overconfidence provided a mixed picture (see Table 5). In terms of experienced knowledge, we found that hierarchy level and domain-related (ITO) experience were negatively related to overconfidence, while professional experience and general IT experience (in IT departments) were positively related to overconfidence. Finally, objective knowledge could be confirmed to be negatively related to overconfidence, whereas subjective knowledge was positively related to overconfidence.

Table 5. Summary of Results

<table>
<thead>
<tr>
<th>Knowledge Type</th>
<th>Impact on Overconfidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experienced Knowledge</td>
<td></td>
</tr>
<tr>
<td>• Hierachy Level</td>
<td>Negative</td>
</tr>
<tr>
<td>• Professional Experience</td>
<td>Positive</td>
</tr>
<tr>
<td>• Experience in IT Departments</td>
<td>Positive</td>
</tr>
<tr>
<td>• ITO Experience</td>
<td>Negative</td>
</tr>
<tr>
<td>Objective Knowledge</td>
<td>Negative</td>
</tr>
<tr>
<td>Subjective Knowledge</td>
<td>Positive</td>
</tr>
</tbody>
</table>

Discussion

In this preliminary study, we investigated the relationship between different knowledge types and overconfidence in IT investment decisions. In doing so, we aimed to find out whether IT decision makers suffer from overconfidence and which kinds of knowledge are positively or negatively related to overconfident behavior. We used IT outsourcing decisions as a surrogate for IT investment decisions,
since these decisions play a major role in the strategic arsenal of today’s organizations (Benamati and Rajkumar 2002; Gorla and Mei Bik 2010). By showing that different knowledge types seem to significantly affect IT managers’ overconfidence in their decision-making behavior, a theoretical contribution of this study is a first step towards an advancement of our understanding of decision-making distortions in the context of IT investments. As we show, IT decision makers’ knowledge does not reduce overconfident behavior per se. Knowledge can be a boon and a bane at the same time because it can simultaneously have beneficial and detrimental effects on overconfidence. In the following, the practical and theoretical implications of this preliminary study are presented according to the three different types of knowledge that may function as important indicators of overconfidence.

We showed that only specific types of experienced knowledge, in our case previous IT outsourcing experience and higher hierarchical levels, are positively related to hit rates which in turn indicate lower overconfidence. These subjects are more aware than others of the limits of their knowledge. Hence, they broaden their intervals to heighten their hit rates. Professional or IT experience in general does not lower overconfidence. Rather, subjects with a lot of IT and professional experience seem to overestimate their knowledge in IT-relevant topics like ITO. Due to this illusory knowledge, they scale down their interval size, which leads to lower hit rates. Our findings, therefore, only partially confirm former overconfidence studies in the context of IT investment decisions. McKenzie et al. (2008), for example, showed that experts generally narrow their interval size which also reduces their hit rate. Based on our more nuanced definition of experience, we believe that we can show that this is only the case for rather nonspecific types of experience, such as professional experience or general IT experience. Only very domain-specific types of knowledge (in our study ITO knowledge) or a high position (i.e., hierarchy level) in the (IT) organization seem to ensure that IT managers are able to reduce the distorting effects of overconfidence by broadening their intervals to raise their chance of getting a hit. In practice, these results may help staffing managers in their hiring processes to better gauge job applicants’ level of overconfidence. Furthermore, the composition and arrangement of teams that regularly make important IT decisions in their companies can be informed by our findings. Team members with a lot of work and/or IT experience are not automatically qualified to make proper IT decisions in specialized fields like ITO. Hence, if there is no real domain expert in a team, it would not seem unreasonable to seek advice from external consultants with domain-specific expertise.

The objective knowledge of IT managers was found to be a double-edged sword in terms of affecting overconfidence. As hypothesized, IT managers with very low levels of objective knowledge indeed demonstrated high levels of overconfidence and thus inflated self-assessments as indicated by a considerably strong over-estimation of their performance (i.e., better-than-average effect). With growing objective knowledge, however, IT managers reduced the gap between self-assessments and their actual performance and thus better estimated their own abilities. Further, IT managers with high objective knowledge strongly underestimated their actual performance and thus did not demonstrate overconfidence. According to psychological literature, they fall prey to the so-called false-consensus effect (Ross et al. 1977). Simply put, these participants assume that because they performed so well, their peers must have performed well likewise. This would have led top-quartile participants to underestimate their comparative abilities (i.e., how their self-reported knowledge compares with that of their peers), but not their absolute knowledge (i.e., interval error). For practitioners, the results show that a considerable share of IT decision-makers is not aware of the fact that their actual decision-making abilities are worse than their own self-assessments. Overly hasty or misleading decisions based on wrong estimates or assumptions may be the result. On the other hand, as we have seen from our results, very competent IT decision-makers who perform better than the average underestimate their abilities considerably. This could result in unnecessary caution about making a decision leading to tentative decision-making, longer decision processes and/or lost opportunities. In either case, IT managers should regularly get performance feedback from various sources (e.g., superiors, peers, external consultants) and engage in group debates to expose them to new experiences and viewpoints and ultimately bring self-assessment of their knowledge and actual knowledge into balance.

In terms of subjective knowledge, we found support for our hypothesis that subjective knowledge of IT decision-makers is positively related to their overconfidence. IT managers who view themselves as above-average in their skills, performance and decision success rate depicted a significantly higher (illusory) control position than IT managers who consider themselves as below-average. They seem to think they can control future events or believe that events in the past were foreseeable from the beginning. However,
this illusory control position can result in overly risky decisions. IT decision-makers that show high subjective knowledge thus have to be careful that they do not suffer from illusory control over future events due to their experience. To mitigate the risks of illusion of control and develop a sharper sense of how much they really can control, decision-makers should be exposed to accurate, timely, and precise feedback (e.g., by superiors, colleagues or external experts) that introduces a safeguard against their own self-assessments. In addition, appropriate measures of holding decision-makers (and their supporting teams) accountable for the consequences of their decisions may force them to confront the feedback, recalibrate their perceptions about their own knowledge, and temper their (over-)confidence accordingly.

**Limitations, Future Research and Conclusion**

This study is subject to several limitations. First, our study is based on a cross-sectional design, which is limited to a single point of time. It was therefore not possible to observe a change in overconfident behavior over time. Future studies could examine overconfidence in a longitudinal setting. In combination with an in-depth analysis of the different knowledge types this could, for example, lead to a more thorough understanding of how overconfidence triggered by knowledge gaps affect real decisions. Second, our survey included just a small set of questions, which was limited due to time constraints, connected to survey studies with high-level decision makers in companies. Nevertheless, the number and types of questions were carefully selected based on previous overconfidence studies and tested for reliability and validity. Future research could, however, attempt to include more questions to investigate the impact of different knowledge types on miscalibration, the better-than-average effect and illusion of control. In addition, more sophisticated statistical tests should be conducted to analyze not only relationships but also the causality between the knowledge and overconfidence variables. Third, the study used IT outsourcing decisions as surrogate for IS investment decisions. In further studies other examples of IS investment decision like enterprise software purchase decisions (e.g., ERP-Systems) or enterprise architecture decisions (e.g., ITIL adoption) should be used to increase the generality of our findings. Finally, our study focused on just one prominent type of cognitive bias in IT decision-making. As previous research in psychology and sociology has shown, several other (e.g., cognitive, social) biases (e.g., framing, confirmation or groupthink biases) can hamper sound decision-making (Finkelstein et al. 2008). Although IS researchers have already begun to include non-rational biases into their research models (e.g., Cheng and Wu 2010; Kim and Kankanahalli 2009; Iacovou et al. 2009), we feel that there are plenty of biases that have not been addressed in the context of IT decision-making but would advance our understanding of important IT-related phenomena.

In conclusion, IT managers in organizations need to become more aware of the role of different knowledge types and their influence on overconfidence in decision-making. Today’s complex, volatile, and fast-paced business and technological environment is placing extraordinary stress on IT decision-makers. Unfortunately, in the quest to be ever more efficient and productive, IT managers often become focused largely on fast and frugal task performance. As a byproduct, they often fail to reflect on the consequences of unsupported confidence in their decisions and the possible factors triggering their overconfidence. To overlook or ignore overconfidence and negative effects, however, means that an IT department or even the entire organization may pay a significant price when it comes to make sound IT investment decisions.

**References**


General Topics


## Appendix

### Table 1. Questions related to Experienced Knowledge

<table>
<thead>
<tr>
<th>Questions</th>
<th>Response categories</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>What is your current level of hierarchy?</td>
<td>1 = Lower; 2 = Middle; 3 = Upper Mgmt.</td>
<td>Based on several studies (e.g., Forbes 2005; McKenzie et al. 2008; Menkhoff et al. 2006; van de Venter and Michayluk 2008)</td>
</tr>
<tr>
<td>What is your total professional experience?</td>
<td>In years</td>
<td></td>
</tr>
<tr>
<td>What is your experience in IT departments?</td>
<td>In years</td>
<td></td>
</tr>
<tr>
<td>What is your ITO experience?</td>
<td>ITO decisions involved in.</td>
<td></td>
</tr>
</tbody>
</table>

### Table 2. Questions used in Calibration Study*

<table>
<thead>
<tr>
<th>Knowledge Questions**</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>What percentage of German firms outsource their data centers?</td>
<td>All knowledge questions were adapted from two current IT outsourcing surveys (Orange Business Services 2009; Messerschmidt et al. 2008)</td>
</tr>
<tr>
<td>What percentage of IT decision-makers see “best practices” as very important for ITO?</td>
<td></td>
</tr>
<tr>
<td>What percentage of IT decisions-makers would consult strategic advisors for ITO decisions?</td>
<td></td>
</tr>
<tr>
<td>What percentage of a firm’s total IT budget is expended on IT outsourcing?</td>
<td></td>
</tr>
<tr>
<td>What percentage of German companies expect cost reductions from IT outsourcing?</td>
<td></td>
</tr>
</tbody>
</table>

** Self-Assessment of Performance

Compared to your peers (i.e., other IT decision-makers), how well do you think you scored? Please indicate below the percentage of your peers that you think you have outperformed in terms of providing small interval errors. [The authors: Interval error was explained to the participants during the calibration study]. For example, if you think you scored better than 90% of your peers, then move the slider to 90. Or if you think you scored better than 15% of your peers, move the slider to 15.

* Note that we derived measures (i.e., hit rate, interval size and error) for Miscalibration, Objective Knowledge and the Better-than-Average effect from the calibration study

** For all knowledge questions, respondents had to provide a low and a high estimate that they were 90% certain to capture the correct answer

### Table 3. Questions related to Subjective Knowledge

<table>
<thead>
<tr>
<th>Questions</th>
<th>Scale</th>
<th>Source</th>
<th>Interitem Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regarding ITO decisions, how would you rate your …</td>
<td>7-point Likert scale: 1 (much worse than the average) - 7 (much better than the average)</td>
<td>Adapted from Larrick et al. 2007; Menkhoff et al. 2006</td>
<td>α=.775</td>
</tr>
<tr>
<td>(1) … skills …</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) … performance …</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) … success …</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>… in comparison to other IT decision-makers?</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 4. Questions related to Illusion of Control (Control Position)

<table>
<thead>
<tr>
<th>Questions</th>
<th>Scale</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Most of the news on ITO is not surprising to me.</td>
<td>7-point Likert scale ranging from 1 (totally disagree) to 7 (totally agree)</td>
<td>Adapted from Burger and Cooper (1979)</td>
</tr>
<tr>
<td>When a service provider does not meet the requirements as arranged, it is not surprising to me.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>When one of my ITO decisions meets all the requirements, it is due to my good planning.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most of the time I can predict very early if an ITO decision is going to be a success or not.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>