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# Information systems in the 21st century: culture, agility and big data

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**Information systems in the 21st century: Culture, agility and big data**

by

**Manjul Gupta**

A dissertation submitted to the graduate faculty  
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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## ABSTRACT

In the past decade, culture has been a focus of several studies in the information systems (IS) field. While the literature on the role of culture in information systems is growing, due to the breadth of the concept of culture, the research involving culture remains challenging. The main challenge pertains to the definition of culture which is evidenced by the presence of more than 150 definitions of culture in literature, yet there is no consensus on one. Another challenge is the existence of various cultural frameworks, and consequently the presence of multiple measures of culture. However, despite the challenges associated with the lack of agreement on the definition of culture and the existence of various measures of culture, the notion of culture is considered a critical factor to understand the national, organizational, and individual-level behaviors in IS and other business disciplines. This dissertation consists of three studies where each study investigates the role of culture in three different information systems-related contexts. The first study focusses on two national cultures, Indian and the United States, and investigates if deception can be detected across cultures, especially when the communication between individuals is mediated by computers. The second study investigates the relationship between different forms of organizational culture (group, developmental, rational, and hierarchical) and the implementation of agile practices, which in turn may lead to organizational creativity. The third study explores the role of data-driven decision making culture, which is defined as a culture in which decisions are made based on data rather than on the beliefs or opinions of organizational members, in creating a firm-specific big data capability.

## CHAPTER 1. INTRODUCTION

In the past decade, culture has been a focus of several studies in the information systems (IS) field. While the literature on the role of culture in information systems is growing, due to the breadth of the concept of culture, the research involving culture remains challenging (Leidner and Kayworth 2006). The main challenge pertains to the definition of culture. According to Kroeber and Kluckhohn (1952), there are more than 150 definitions of culture in literature, yet there is no consensus on one. For example, Hill (2005) describes culture as a system of values and norms that are shared among a group of individuals and that when taken together constitute a design for living. According to Hofstede (1980), culture is “the collective programming of the mind which distinguishes the members of one human group from another” (p. 260). Doney et al. (1998) applied the “national” label to culture to differentiate the character of a society from corporate culture.

Another challenge is the existence of various cultural frameworks, and consequently the presence of multiple measures of culture (e.g., Hall and Hall 1976; Hofstede 1980; House et al. 2002; Quinn and Rohrbaugh 1983; Schein 1990b). For example, Hall and Hall (1976) conceptualize culture with respect to the context, which is the extent to which a society prefers to use high context messages (i.e., less explicit) over low context (i.e., highly explicit) messages in everyday communication. The Hofstede’s national cultural framework proposes five cultural dimensions: individualism, power distance, uncertainty avoidance, masculinity, and long-term orientation. A more recent national cultural framework was presented by House et al. (2002), who based on their analysis of data collected from 62 countries (also known as the GLOBE study), identified nine cultural dimensions: performance orientation, future orientation,

assertiveness, power distance, humane orientation, institutional collectivism, in-group collectivism, uncertainty avoidance, and gender egalitarianism. Quinn and Rohrbaugh (1981) proposes four forms of organizational culture: group culture, developmental culture, rational culture, and hierarchical culture.

Despite the challenges associated with the lack of agreement on the definition of culture and the existence of various measures of culture, the notion of culture is considered a critical factor to understand the national, organizational, and individual-level behaviors in IS and other business disciplines. For instance, Hill et al. (1998) investigated how national culture influenced transfer of technology from developed countries to developing countries. Alavi et al. (2006) studied the impact of organizational culture on knowledge management practices. Srite and Karahanna (2006) examined the role of individuals' espoused cultural values in their beliefs on technology acceptance. Consistent with this stream of research, this dissertation attempts to extend the existing literature on cultural studies in the IS field by studying the role of culture in three different settings.

The first study focusses on two national cultures, Indian and the United States, and investigates if deception can be detected across cultures, especially when the communication between individuals is mediated by computers. The second study investigates the relationship between different forms of organizational culture (group, developmental, rational, and hierarchical) and the implementation of agile practices, which in turn may lead to organizational creativity. The third study explores the role of data-driven decision making culture, which is defined as a culture in which decisions are made based on data rather than on the beliefs or opinions of organizational members, in creating a big data capability. Besides data-driven decision making culture, several other resources, such as managerial and technical skills and

basic resources (e.g., adequate investments, sufficient time), were suggested as important resources needed to build a firm-specific big data capability. Next, I briefly describe each of the three studies.

### Study 1: The Effects of Media and Culture on Deception Detection

Computer-mediated communication (CMC) has become so pervasive that anyone with an Internet connection and a computer (or a smart phone) can communicate with others regardless of their physical location. While there are several benefits of using new forms of CMC-based media (e.g., emails, VoIP), the new technologies are often exploited by con artists to deceive individuals over the Internet. Part of the reason for this can be attributed to the anonymous environment of the Internet, which offers online con artists almost absolute freedom to indulge in deceptive activities without a fear of getting caught. Moreover, as computers continue to become cheaper and with the increasing number of the Internet users around the globe, more and more people are likely to use CMC-based media to communicate with others, not only within their own culture, but also with people from other cultures.

According to a corpus of research in the communication field, approximately one-third of everyday communication tends to be deceptive in some form (Hancock et al. 2004). While there are some studies that have examined deception and its detection across cultures (Al-Simadi 2000; Bond and Atoum 2000), these studies were conducted more than a decade earlier when the Internet-based communication technologies were in a nascent stage. In addition to this, while IS researchers have presented several theories to classify different media (e.g., media richness, channel expansion, and media synchronicity), the majority of this research has assumed all communication to be honest. Thus, relatively little is known when individuals engage in

deceptive CMC. Drawing upon leakage theory (Ekman and Friesen 1969; Ekman and O'Sullivan 1991), media synchronicity theory (Dennis et al. 2008), and the Hofstede' framework for national culture, this study examines the following research questions: RQ1: How do CMC-based media (audiovisual, audio only, video only, and text only) impact the ability of individuals to detect deception? RQ2: How do cultural and language differences affect the ability of individuals to detect deception across cultures that share a language and cultures that do not?

A controlled laboratory experiment was conducted in which 112 American business undergraduate students were asked to judge the veracity of one of three stimulus sets featuring either American or Indian students. While all American students spoke in English, half of Indian students spoke in Hindi, and the other half spoke in English. Each stimulus consisted of 32 snippets such that 16 were honest and 16 were dishonest. Of the 32 snippets, six were text only, six were audio only, six were video only (meaning no sound), and the remaining six were audiovisual. In sum, there were three treatment conditions: 1) Indians speaking in English, 2) Indians speaking in Hindi, and 3) Americans speaking in English, and four levels of media (text, audio, video only, and audiovisual). Based on data collected from the experiment, the main effects of treatment and media, along with their interaction, were tested on individuals' ability to successfully detect deception, which was calculated as the percentage of dishonest snippets that were correctly judged dishonest.

### Study 2: The Impact of Organizational Culture On Agile Practices

Organizations in almost all industries have increasingly faced some turbulence in their external environments (Karimi et al. 2004). This turbulence often leads to the need for developing information systems for new business requests and unexplored problem domains



(Tiwana and McLean 2003). Agile systems development (ASD) was specifically designed for today's uncertain market conditions where speed and flexibility are considered critical for organizations to survive. Unlike traditional waterfall systems development methodologies (SDM), which are suited for stable and foreseeable markets, ASD enables the development and release of softwares in Internet time.

In the past decade, IS scholars have expended considerable effort to understand obstacles to successful ASD implementation in organizations. This stream of research often cites organizational culture as a significant barrier to ASD (Cockburn and Highsmith 2001; Tolfo et al. 2011). Consequently, the majority of this research has focused on recommending the optimal agile culture, which is collaborative, less hierarchical, and people-centric. However, since organizations with varying cultural orientation and in different industrial sectors have successfully embraced ASD, this study proposes that agile practices can be implemented in a range of organizational cultures. Additionally, this study dimensionalized ASD into technical and social agile practices. While engineering-based systems development practices such as coding standards, continuous integration, unit testing, refactoring, and collective ownership, are defined as technical agile practices, practices such as daily standup, retrospective meetings, access to product manager, and pair-programming that encourage communication among employees are defined as social agile practices.

Drawing on the competing values framework for organizational culture, which proposes four types of organizational culture (group, developmental, rational, and hierarchical), the relationships between different cultural forms and technical and social agile practices are investigated. In a further attempt to assess the benefits of ASD, this study proposes a positive relationship between ASD and organizational creativity, which refers to the generation of new

products (or services). In sum, this study addresses the following research questions: RQ1: How can different forms of organizational culture affect the use of technical and social agile practices? RQ2: How do technical and social agile practices influence organizational creativity?

To answer these research questions, a survey of agile managers in 179 US-based organizations was conducted. The participants were randomly selected from an online LinkedIn community of over 12,000 agile practitioners, and they represented a variety of industries (e.g., computers, financial services, internet, communications and utilities). Data was analyzed using partial least squares (PLS) statistical technique, which is based on a components-based structural equation modelling.

### Study 3: Towards the Development of a Big Data Capability

The era of big data, which refers to unstructured, diverse, and fast moving data, has begun where organizations in all industries are increasingly collecting enormous volumes of data. While the research into the economic benefits of big data is in a nascent stage, organizations around the globe have been heavily investing in big data initiatives. For instance, according to Gartner's (2013) survey of 720 firms worldwide, 64% of organizations (an increase of 8% over the previous year) have already invested in or plan to make investments in big data. However, we know from prior studies that investments alone do not generate competitive advantage; instead firms need to create capabilities that rival firms find hard to match (Bharadwaj 2000; Carr 2003). In this sense, investments represent one such resource that is needed by the firm to create a big data capability, which this study defines as a firm's ability to assemble, integrate, and deploy its big data-specific resources.

Moreover, there is a widely-held perception that big data projects fail because most organizations do not have the right technical tools to harness its potential; however, some have recently started to raise doubts about this popular opinion (McAfee and Brynjolfsson 2012). For instance, Lavalle and colleagues (2014) indicate that the reasons why big data projects are often unsuccessful relate to organizational culture rather than to the data attributes and technology. Similarly, Ross, Beath, and Quaadgras (2013) assert that culture can impede (or enhance) an organization's ability to benefit from big data. To do so, organizations need to have a data-driven decision making culture in which decisions are made in response to the insights extracted from data rather than on the opinions or beliefs of senior executives (McAfee and Brynjolfsson 2012; Ross et al. 2013). In addition to data-driven culture, the success of big data projects is also dependent on the wisdom and business acumen of managers and big data-specific skills of employees (Chen et al. 2012; LaValle et al. 2014)

Drawing on the resource-based view of the firm and the recent work in big data, this study identifies various resources (e.g., technology, data, investments, and managerial and technical skills) that are needed by firms to build a big data capability. Further, using Grant's (2010) classification of organizational resources, this study categorizes these big data-specific resources into tangible, human, and intangible types. Specifically, this study will answer the following research question: "What are the resources needed to create a firm-level big data capability?" Additionally, this study proposes and validates an instrument to measure a big data capability of the firm.

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## CHAPTER 2. THE EFFECTS OF MEDIA AND CULTURE ON DECEPTION DETECTION

### Abstract

Over the years, a substantial amount of research has been conducted pertaining to deception and its detection. However, the majority of this research has examined deception in face-to-face communication, and thus very little is known about deception and its detection when communication is mediated by computers. With the diffusion of the Internet, more and more people around the world are making use of computer-mediated communication (CMC) tools (e.g., emails, VoIP) to interact with others within and outside of their own culture. Given that approximately one-third of daily communication tends to be deceptive in some form (Hancock et al. 2004), the amount of deception in cross-cultural communication that is mediated by computers is likely to rise. Thus, to gain more insights about detection of deception in computer-mediated cross-cultural communication, we asked 112 American undergraduate students to detect lies from stimulus sets featuring Indians speaking in English, Indians speaking in Hindi, and Americans speaking in English. These stimulus sets were presented in one of four CMC-based media: audiovisual, audio only, video only, and text only. The results of our experiment indicate that participants were more successful at detecting deception from an audio only medium than from audiovisual, followed by video only, and text only media. Further, participants were better able to detect deception from the stimulus sets featuring Indians speaking in English, followed by Indians speaking in Hindi, and Americans speaking in English.

## Introduction

The unprecedented growth in computer-mediated communication (CMC) technology has made this world a smaller place; however, the ubiquity of CMC-based media (e.g., email, VoIP, SMS, instant messaging) and the low cost associated with their use have spawned a whole new world of deception. For example, consider the Skype call scam, in which Skype users receive a call from someone pretending to be the company's support representative and asking them to install an antivirus program to protect their Windows machine (Kirk 2012). Though MIS researchers, over the years, have been actively developing and examining the theories of computer-mediated communication (e.g., media synchronicity theory, media richness theory), the majority of this research has assumed all communication to be honest. Thus, relatively little is known when individuals engage in deceptive communication that is mediated by computers. Even less is known when computer-mediated deceptive communication involves participants, who are from different cultures and speak different languages.

As computers continue to become cheaper and dispersed all over the world (Friedman, 2005), more and more people are making use of CMC-based media to communicate with others, not only within their own culture, but also with people from other cultures. According to some estimates, approximately one-third of daily communication is deceptive (George and Robb, 2008); thus, it will be safe to assume that with decreasing computers prices and increasing diffusion of the Internet, the amount of deception in computer-mediated communication is likely to escalate. Some past research in the communication discipline has investigated the ability of individuals to detect deception within and across cultures. For example, Al-Simadi (2000a) asked Malaysian and Jordanian judges to detect deception from the videotapes featuring Malaysian and Jordanian participants. While half of Malaysian participants spoke in Arabic, the other half spoke



in English. All Jordanian participants spoke in Arabic. Overall, judges were better able to detect deception in the other culture (57% success rate) than within their own culture (52%).

Surprisingly, Al-Simadi did not report any findings due to language differences. While these findings provide evidence that deception can be detected across cultures, they fail to shed light on the relationship between language and deception detection.

While there are a few studies that have examined the impact of language on deception detection, these studies did not include participants from multiple cultures. For example, Broadhurst and Cheng (2005) investigated the ability of Hong Kong Chinese to detect deception in their first language (Cantonese) and second language (English). Participants had higher detection rates when their peers spoke in English compared to when they spoke in Cantonese. Since Broadhurst and Cheng's (2005) study consisted of only Hong Kong Chinese participants, the findings are difficult to generalize to other cultures.

Besides looking at the impact of culture and language on deception detection, some limited research has also investigated the relationship between media and deception detection. For instance, the experiments by Al-Simadi (2000a) and Bond and Atoum (2000) reveal that judgments from audiovisual or audio only media are expected to be more accurate than the ones made from video only media. On the contrary, Burgoon et al. (2003) suggest that people get overwhelmed with the presence of excess cues in audiovisual media, and thus are unable to differentiate between truth-telling and lie-telling behaviors. According to them, deception detection is likely to be more accurate from audio only media than from audiovisual media. These mixed findings in the literature and the lack of studies examining the relationship between media and deception detection call for additional research to investigate the relationship between different CMC-based media and deception detection.

Based on the discussion provided in this section so far, we present two research questions: *How do CMC-based media (audiovisual, audio only, video only, and text only) impact the ability of individuals to detect deception? How do cultural and language differences affect the ability of individuals to detect deception across cultures that share a language and cultures that do not?* To investigate our research questions, we conducted a controlled laboratory experiment in which we asked 112 business undergraduate students to judge the veracity of one of three stimulus sets featuring either American or Indian students. While all American students spoke in English, half of Indian students spoke in Hindi, and the other half spoke in English. Each stimulus consisted of 32 snippets (16 honest and 16 dishonest), and each snippet was presented in one of four media formats: audiovisual, video only, audio only, and text only.

In the next section of the paper, we first review the literature on deception, followed by the relationship between CMC and deception. Next, we review the literature on culture and language as they relate to deception and its detection. Next, we present our hypotheses and describe our research methods and data analysis. The paper ends with a discussion of findings, followed by implications for practice and research.

### **Literature And Hypotheses**

We start this section by first defining deception, which is “a message knowingly transmitted by a sender to foster a false belief or conclusion by the receiver” (Buller and Burgoon, 1996, p. 205). Though a few researchers like Bok (1978) make a distinction between deception and lying, consistent with Vrij (2000) and DePaulo et al. (2003), we use these two terms interchangeably in this paper. Studies of deception suggest that people lie for various reasons. For example, doctors lie to their patients about dosage (Jackson, 2001; Backhurst,

1992), job applicants lie during interviews (Weiss and Feldman, 2006), potential visitors lie during visa interviews (Ekman and Matsumoto, 2009), adolescents lie to their parents to express a sense of autonomy (Arnett et al., 2004), individuals lie to romantic partners for intimacy (Cochran and Mays, 1990), and salespeople lie during trade negotiations to further their own personal interests (Aquino and Becker, 2005). Thus, lying is indeed a common social act.

However, despite lying being such a common occurrence, people in general are poor detectors of deception. The likelihood of successfully detecting lies is analogous to flipping a coin in which there is an even odds chance (DePaulo et al., 1997; Kalbfleisch, 1994; DePaulo, Zuckerman, & Rosenthal, 1980; Vrij, 1994; Millar & Miuar, 1995). Interestingly, even experts such as law enforcement personnel and policemen perform no better than laymen when it comes to detecting deception (Ekman, 1985). Kohnken (1987) asked police officers to detect lies from a mix of honest and dishonest videotapes of eyewitnesses. Despite being instructed to pay close attention to leaked verbal (e.g., tone of voice, slip of the tongue) and non-verbal cues (e.g., facial expressions, gestures like wringing one's hands), police officers performed no better than non-experts.

One possible reason for this is truth bias, which refers to the tendency of people to trust others by default until given a chance or reason to think otherwise (Miller and Stiff, 1993). According to Vrij and Baxter (1999), people in general come across more honest statements than dishonest statements in everyday life; thus, they tend towards judging others as being more truthful than deceitful.

Another reason that impedes people's ability to detect deception is their heavy reliance on false stereotypes about lying behaviors (Hartwig and Bond, 2011). Despite a plethora of studies suggesting that there is no link between eye aversion and lying (e.g., DePaulo et al.,

2003; Miller & Stiff, 1993; Zuckerman et al., 1981), averting eye contact is still considered the most prominent pan-cultural stereotype regarding deceptive behavior (Aavik et al., 2006). Due to these challenges, detection deception detection rates rarely exceed chance level.

However, over the years, a significant amount of research on deception and its detection has yielded interesting insights. The majority of this research has linked deception detection to the identification of reliable cues to deception. This stream of research has primarily relied on the *leakage theory*, which asserts that deception is such a complicated thing that deceivers often leak out cues in the form of verbal and non-verbal behaviors (Ekman and Friesen, 1969; Ekman, 1985). If people are observant to verbal and non-verbal behaviors of others, deceivers stand a better chance of getting caught. While some deception literature follows Darwin's (1872/1965) assumption of universality of facial expressions, researchers like Kraut (1980) argue that verbal and non-verbal behaviors of deception are not uniform, as they tend to vary "depending on the topic of deception, the cognitive difficulty of the deception, the emotions generated during the deceptive attempt and a particular deceiver's limitations" (p. 212). However, in their quantitative analysis of 45 studies, Zuckerman and Driver (1985) found some consistency across the studies linking behavioral cues to deception. Of the twenty four cues analyzed by them, they were able to separate fourteen into truth-telling and lie-telling behaviors. In another study, DePaulo et al. (2003), based on their meta-analysis of 120 independent samples, reported 158 different cues to deception. Further, they found that liars "tell less compelling tales" and are more tensed than truth-tellers (p.74). Similarly, highly motivated liars are expected to give away more non-verbal cues (DePaulo and Kirkendol, 1989).

Besides leakage theory, interpersonal deception theory (IDT), proposed by Buller and Burgoon (1996), has received significant attention from scholars interested in studying

deception. IDT treats deception as a dyadic interactive communication event between a sender and a receiver. According to IDT, deception detection is dependent on many factors, such as relationship, motivation, and whether communication is face-to-face (FtF) or mediated. In a similar vein, Carlson et al. (2004) suggest that “successful detection of deception is determined by the participants involved, their relationship, the design and delivery of the deception, and the medium used to convey the communication” (p.14). Thus, communication medium is an important factor that may influence successful deception detection. Buller and Burgoon (1996) further assert that different media, based on their capability to transmit various social context cues, place different kinds of conversational demands on the participants involved in communication.

In face-to-face deception, participants have full access to the range of social information available in environmental, visual, auditory, and verbal channels. By contrast, less interactive contexts restrict channel and information availability, producing a limited cues environment that may alter behaviors and perceptions (Buller and Burgoon, 1996, p.212).

Given that different forms of media may influence individuals’ behavior and perceptions in different ways that in turn are likely to impact their detection capabilities, it is important to first understand the differences among various media forms.

### **CMC and deception**

The unique capabilities of the Internet have completely transformed the traditional means of communication (e.g., FtF, snail mail) into computer-mediated communication, which is an umbrella term that is often used to describe a variety of Internet-based media. One of the early definitions of CMC was proposed by Walther (1992), who defined CMC as “synchronous [simultaneous] or asynchronous [delayed] electronic mail and computer conferencing, by which senders encode in-text messages that are relayed from senders' computers to receivers” (p.52).

To completely understand the meaning of this definition and differentiate among various CMC-based media, it is important to understand the notion of synchronicity. Synchronicity is the extent to which individuals can simultaneously work towards achieving common ground (Carlson and George, 2002; Dennis et al., 2008). Based on the degree of synchronicity, a medium can be classified into either synchronous (e.g., audiovisual based media such as Skype and FaceTime) or asynchronous medium (e.g., text-based media such as emails and instant messaging).

While all cues are available FtF, the number of available cues gets filtered out as the communication medium changes from synchronous to asynchronous (Sproull and Kiesler, 1986; Adkins and Brashers, 1995; Daft, Lengel, and Trevino, 1987; Walther, 1992). Thus, of all CMC-based media, a video-based medium is capable of transmitting the maximum number of cues, while comparatively fewer cues are revealed in an audio-based medium. Even fewer cues can be detected from a text-based medium. Consistent with research discussed so far, Rao and Lim (2000) linked a medium's capability to relay the maximum number of cues to more successful deception detection. They further ranked different media across fourteen reliable cues to deception that were suggested by Zuckerman and Driver (1984).

Table 1. Cues to deception across various media (Rao and Lim, 2000)

Behavior	Video	Audio	Written Modes
Visual			
Pupil dilation	Detectable		
Gaze			
Blinking	Detectable		
Smiling			
Facial segmentation	Detectable		
Head movements			
Gestures			
Shrugs			
Adaptors	Detectable		
Foot & leg movements			
Postural shifts			
Bodily segmentation	Detectable		

Table 1 continued

Paralanguage			
Latency			
Response length	Detectable	Detectable	Detectable
Speech rate			
Speech errors	Detectable	Detectable	Detectable
Speech hesitations	Detectable	Detectable	In real-time interactive writing, may be detectable
Pitch	Detectable	Detectable	
Verbal			
Negative statements	Detectable	Detectable	Detectable
Irrelevant information	Detectable	Detectable	Detectable
Self-references			
Immediacy	Detectable	Detectable	Detectable
Leveling	Detectable	Detectable	Detectable
General			
Discrepancy	Detectable	Partially detectable	Partially detectable

According to Rao and Lim (2000), every medium is capable of transmitting at least a small subset of deceptive cues, and thus deception can be detected across all forms of media such that “a written statement may not have nonverbal cues, but inconsistencies in a written narration will reveal deception” (p.6). However, a medium’s capability (or synchronicity) to transmit a wide variety of verbal and non-verbal cues influences the accuracy of correctly identifying deception such that availability of more cues should be translated into higher deception detection rates and vice versa (Rao and Lim, 2000). Since people feel more confident while making deception judgments from synchronous media than from asynchronous media (Carlson and George, 2002), deception detection should be more accurate when the judgments are made from video-based synchronous media than the ones that are made from asynchronous media. Based on this, we hypothesize:

**H1: Deception detection will be more accurate when the judgments are made from audiovisual media than those made from video only, followed by audio only, and text only media.**

Having developed the hypothesis for our first research question, we next review the role of cultural and language in deception detection.

### **Impact of culture and language on deception**

Culture is “the collective programming of the mind which distinguishes the members of one human group from another” (Hofstede, 1980, p. 260). According to Hofstede (2010), there is no single universal culture, and people around the world have major differences in terms of how they think, feel, and act. Studies of deception across cultures (see Table 2) indicate that people from different cultures have different beliefs about deception. What would be considered deceptive in one culture might not be treated in the same way in another culture. For example, making false promises or lying during business negotiations is a common practice in collectivistic Asian cultures; however, these practices are considered highly improper in individualistic Western cultures (Triandis et al., 2001; Li et al., 2006; Zarkada-Fraser and Fraser, 2001). Additionally, a corpus of cross-cultural studies indicates that people from different cultures significantly diverge in terms of their verbal and non-verbal behaviors. One such example is tongue showing. While Europeans use it for teasing, people in Tibet use it as a sign of greeting (Feyereisen and de Lannoy, 1991). Another example is “forming an O-shape with the thumb and the index finger,” which depending on the culture may either indicate OK, money, zero, or an insult (Feyereisen and de Lannoy, 1991, p.7).

While these examples reflect culture-specific differences, there are certain verbal and non-verbal behaviors that accompany the spoken language. For example, while the majority of English language speakers express emotional states such as anger and annoyance through the use of high intensity tone, the Siouan language, spoken by the Dakota people, “has formal linguistic expression by means of a particle added at the end of the sentence” to show their displeasure



(Pennycook, 1985, p.269). Similarly, while French and Spanish language speakers use hand gestures and other bodily actions to express themselves, British English speakers consider gesturing inappropriate (Graham and Argyle, 1975).

Based on the discussion so far, it can be noted that there are culture-specific and language-specific verbal and non-verbal behaviors. A question that can be raised here is: Are culture and language two separate entities? According to Brown (1994):

A language is a part of a culture and a culture is a part of a language; the two are intricately interwoven so that one cannot separate the two without losing the significance of either language or culture (p.65).

Table 2. Deception across cultures

Study	Countries	Select Findings
Li, Triandis, & Yu 2006	Singapore	Positive correlation between deception and collectivism in organizational business negotiations
Seiter & Bruschke, 2007	China & US	Americans experienced more guilt over lying than Chinese participants.
Mealy et al 2007	Ecuador & US	Euro-American participants perceived lying to be more acceptable than Ecuadorians
Wang & Leung 2010	Singaporean Chinese, US & Taiwan	Americans prized honest behavior more than they reprimanded deceptive behavior; however, East Asians did not show any deviation between the two
Sweet et al 2010	China & US	Chinese children found lying to hide a group's misbehaviors less acceptable than did American children
Fu et al 2011	China & US	Chinese participants perceived lying more favorably than Americans for modest behavior
Choi et al. 2011	Korea & US	Koreans might perceive lying for a friend less negatively as opposed to Americans
Zhang 2013	China & US	Americans considered emotional deception (intentional display of emotions to influence others) more acceptable than Chinese negotiators, while Chinese approved the use of informational (deliberately misrepresenting the information) deception more than American negotiators.

Table 2 continued

Heyman et al. 2013	China & US	Chinese parents (98%) more likely to lie to their children to encourage behavioral compliance than American (84%) parents
Hamilton & Kirwan 2013	Ireland & US	Online dating profiles of Irish males were found more deceptive than American profiles.
Phan 2014	US	Collectivistic individuals more likely to use blatant, self-serving, and altruistic lies than individualistic individuals to have sex. Additionally, individualistic individuals more likely to lie to avoid confrontation than collectivistic individuals.
Banai et al. 2014	Israel & Kyrgyzstan	Kyrgyzstanis more likely to endorse ethically questionable negotiation tactics (i.e., pretending, deceiving, & lying) than Israelis.

Table 3. Deception detection across cultures

Study	Countries	Select Findings
Bond et al 1990	Jordan & US	Successful lie detection within cultural groups but not across
Bond & Atoum 2000	US, Jordan & India	Lies successfully detected across cultures that share a language and cultures that do not
Al-Simadi 2000	Jordan & Malaysia	Individuals detected 52% of lies within their own cultures & 57% between cultures
Cheng & Broadhurst 2005	Hong Kong Chinese	Observers better able to identify deception in their second language than in native language
Evans & Michael, 2013	US Hispanics	Truth detection greater when judging native-speakers; deception detection greater when judging non-native speakers
Da Silva & Leach 2013	Canada	Observers more accurate in detecting truth-telling and lying behaviors in native English speakers than second-language speakers

Despite considerable support pertaining to the inseparability of culture and language in linguistic and cross-cultural studies (e.g., Whorf, 1956; Brown, 1994; Jiang, 2000), the existing research on cross-cultural deception has either examined the impact of cultural differences on deception detection or the role of language differences in detection deception (see Table 3). For

example, Al-Simadi (2000a) found that Malaysian and Jordanian participants were more accurate at detecting lies in the outside culture (57% success rate) than in their own (52%). Though Al-Simadi varied the language in the videotapes by asking all of the Jordanian participants and half of the Malaysians to speak in Arabic and other half of the Malaysian participants in English, he did not report any findings based on language differences.

In contrast, Cheng and Broadhurst (2005) found that Hong Kong Chinese participants were better able to detect deception in their second language, English, than in their first language, Cantonese. Though Cheng and Broadhurst's study provides valuable insights about the role of language in deception detection, given that the study consisted of only Hong Kong Chinese participants, the findings are difficult to generalize to non-Chinese cultures. Recently, two more studies have examined deception detection between native and non-native English speakers. While Evans and Michael (2013) found that observers were more accurate in detecting lies among non-native English speakers than among native English-speakers, Da Silva and Leach (2013) found the opposite. In both these studies, the role of culture was not specifically discussed.

To the best of our knowledge, the only study that investigated the impact of differences due to culture and language on deception detection was conducted by Bond and Atoum (2000). Although the participants in their study were better able to identify lies outside of their cultural group, they did not find significant effects of language on deception detection. While this study and another study by Al-Simadi (2000a) indicate deception detection across cultures, as evident from Table 3, questions examining the simultaneous impacts of language and culture on deception detection remain underexplored.

Substantial research in linguistics asserts that, while speaking in their non-native language, people are likely to adhere to the speaking styles and the norms (e.g., phonological, semantic, syntactic, pragmatic, and prosodic) of their *stronger* native language (Pika et al, 2006; Nicoladis et al., 2005; Efron, 1941; Marcus, 1979; Sherman & Nicoladis, 2004; Ralston et al., 1995; Nicoladis, 2007; Snyder, 1971). Further, different languages have different paralanguages (i.e., the non-verbal elements of the communication) such as pitch, volume, pauses, tone, rhythm, stress, and intonation of speech (Duncan, 1969; Houston, 1984). Thus, it is safe to assume that speakers of a native language should be able to identify any irregularities whenever non-native speakers violate the commonly held norms, styles, and paralanguage elements of the native language.

Given that people, in general, are wary of foreigners (Smith and Bond, 1994) and non-native speakers have a tendency to stick to the linguistic standards of their native language, people are more likely to be suspicious of foreigners when they speak in the native language of the judges than when they speak in their own native language. Based on the discussion so far and the past evidence that deception detection is likely to be more successful in the outside culture compared to within (Al-Simadi, 2000; Bond and Atoum, 2000), we present our second hypothesis:

**H2: American judges will be more accurate at detecting deception when exposed to Indians speaking in English, followed by Indians speaking in Hindi, and Americans speaking in English.**

### Methodology

To investigate the role of media and culture and language on individuals' ability to detect deception, we conducted two controlled laboratory experiments – the pilot study and the main study. For both studies, the research design consisted of two distinct phases: 1) creation of

stimulus sets featuring American and Indian graduate students, and 2) making the veracity judgments. For the pilot study, twenty Indian graduate students were recruited with help from the international student association body at a large Midwestern university. During the experimental sessions, students were asked to apply for a fictional graduate scholarship. They were told that they could enhance their personal achievements or any other information that might increase their chances of getting the scholarship. Completed scholarship applications were compared with students' actual résumés and any enhanced information on the scholarship applications was marked as dishonest. Interviews were then conducted via Skype and were videotaped with the consent of the participants. While half of the Indian participants spoke in Hindi, the other half spoke in English.

The video recordings were then edited to create three stimulus sets, each consisting of 24 snippets such that half were honest and half were dishonest. Each stimulus set was also varied by four media formats: audiovisual, video only, audio only, and text only. Of the 24 snippets, six were text only, six were audio only, six were video only (meaning no sound), and the remaining six were audiovisual. Text only snippets were the transcribed version of the interview video recordings. For Hindi language interviews, the text snippets were translated into English. In total, there were three treatment conditions: 1) Indians speaking in English (or Indian English), 2) Indians speaking in Hindi (or Indian Hindi), and 3) Americans speaking in English (or American English). The American English stimulus set was already available from a previous study (George, et al., 2008).

In the second phase, fifty undergraduate students in a senior-level supply chain course from the same university served as judges in the study. Judges were asked to make veracity judgments in response to one of the three stimulus sets (American English, Indian English, or

Indian Hindi). All of the 24 snippets were presented to the participants in survey instruments, which were created using Qualtrics. Participants judged the veracity of each snippet on a 7-point Likert scale where “1” meant “very honest” and “7” meant “very dishonest.” The seven-point Likert scale was collapsed into a discrete variable such that a selection of 1 to 4 was considered a judgment of truth and a selection of 5 to 7 was considered a judgment of dishonesty. Whenever judges marked a snippet as being dishonest, in the next screen, they were asked to list the indicators that convinced them to judge the person in the snippet as a liar. This process continued until all of the 24 snippets were read, listened, or watched. The dependent variable was deception detection success, which was the percentage of dishonest snippets that were judged dishonest.

The results from the pilot study were encouraging. No major technical problems emerged. For the main study, another twenty Indian students were recruited and their interviews were videotaped. Eight more snippets were added to each of the three existing stimulus sets from the pilot study. Thus, the main study consisted of 32 snippets where 16 were honest, and the remaining half was dishonest. Further, of the 32 snippets, there were eight snippets for each of the four media types: text, audio, video, and audiovisual. Like the pilot study, the same process was followed for the second phase of the main study. Fifty eight undergraduate students in a senior-level supply chain and fifty four undergraduate students in management information systems courses were asked to make veracity judgments in response to one of three stimulus sets on a 7-point Likert scale.

To keep the participants motivated in both the pilot and the main study, participants in the first phase were given \$10 gift cards, while participants who served as judges earned 1% course credit. Precaution was taken to ensure that none of the judges, who participated in the second

phase of the study, knew the participants from the first phase and the participants who served as judges in the pilot study did not participate in the main study.

### Findings

A linear mixed-model ANOVA with repeated measures was run in SPSS (version 21) to investigate the effects of culture and language, and media on successful deception detection. Repeated measure design was chosen because each participant in the second phase of the main study was exposed to 32 different snippets. While question number (1-32) was included as a random factor, treatment condition (Indian English, Indian Hindi, and American English) and media were included as fixed factors. The dependent variable was deception detection success.

Results revealed significant main effects for media and treatment (i.e., culture and language). The interaction effects between media and treatment were also found significant. The summary of results is shown in Table 4, and the mean detection success rates for different media and treatments are shown in Table 5 and Table 6 respectively.

Table 4. Results of mixed-model

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	3422.152	4956.986	.000
Media	3	2441.860	7.030	.000
Treatment	2	3421.187	16.418	.000
Media * Treatment	6	2187.190	4.012	.001

**Dependent Variable:** Deception detection success

Table 5. Deception detection success rates for different media

Media	Mean	Standard Error
Text only	55.5%	.016
Audio only	63.5%	.016
Video only	53.5%	.016
Audiovisual	57.9%	.016

Table 6. Deception detection success rates for different treatments

Treatment	Mean	Standard Error
Indian English	63.3%	.014
Indian Hindi	57.8%	.014
American English	51.8%	.014

Overall, the detection success rate was 55.5%, which was better than chance. To test our hypotheses, we conducted the Bonferroni test to compare the detection rates across different media and treatments. The pairwise comparisons for media found audio only media ( $M = 63.5\%$ ,  $SE = .016$ ) to be statistically different from text ( $M = 55.5\%$ ,  $SE = .016$ ) and video only media ( $M = 53.5\%$ ,  $SE = .016$ ); however, no other statistically significant pairwise differences were observed. Though mean detection success rate for audiovisual ( $M = 57.9\%$ ) was more than video only and text only media, the Bonferroni test did not suggest any significant differences between the three. Based on the leakage theory and the notion of synchronicity, we had proposed that individuals would be more accurate at detecting deception from audiovisual media than from video only, followed by audio only, and text only media. Since participants were better able to detect deception from audio only media compared to either text only or video only media, the ranking proposed in H1 was not supported.

For treatment conditions, the Bonferroni test revealed significant differences between all of the three treatments. Participants were more accurate in detecting deception from the stimulus



sets featuring Indians speaking in English ( $M = 63.3\%$ ,  $SE = .014$ ) than Indians speaking in Hindi ( $M = 57.8\%$ ,  $SE = .014$ ), followed by Americans speaking in English ( $M = 51.8\%$ ,  $SE = .014$ ). Thus, H2 was supported.

To show the interaction effects between media and treatment conditions, we plotted the detection success rates against the treatment conditions for each media type. Careful analysis of the plot suggests that for the snippets presented in text only and video only media, detection rates were highest for American English, followed by Indian Hindi, and Indian English. For audiovisual media, the Indian Hindi treatment was different than both American English and Indian English treatments. The most surprising observation from the plot was for audio only media, which followed a straight parallel line to the x-axis, suggesting no major difference in detection success rates across the three treatments. This suggests that for American participants, deception detection success for audio only snippets did not vary by treatment.

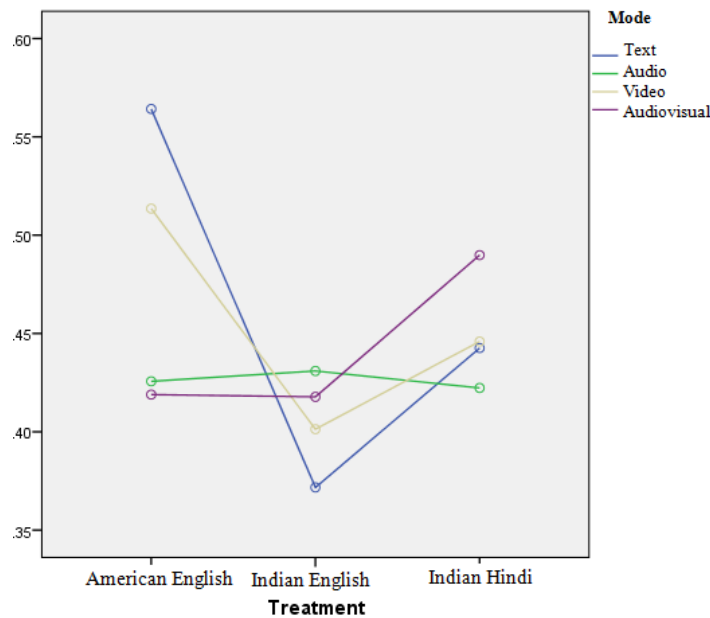


Figure 1. Interaction between Media and treatment

## Discussion

We initially hypothesized that successful detection of deception would be influenced by media's capability to transmit a wide variety of verbal and non-verbal cues. Based on this, we expected that the deception detection rates would be highest for the judgments made from audiovisual media, followed by video only, audio only, and text only media. However, this ranking was not supported. As shown in Table 5, the findings indicate that detection rates are likely to drop as we move from audio to audiovisual to either text or video only media.

Interestingly, the lower detection success from audiovisual media compared to audio only media may be due to the *seeing is believing* visual bias, whereby people get overwhelmed by the excess visual information, resulting in greater levels of truth bias (Burgoon et al., 2003). "Therefore, more is less," and thus deception detection accuracy is likely to be greater when the judgments are made from an audio only medium than from an audiovisual medium (Burgoon et al., 2003, p.10). While there were differences in the mean detection success rates across the four media, only audio media was found statistically different from text and video only media. This implies that, of the three media (audio, text, and video only), individuals have the best chance to detect lies from audio only media.

Consistent with previous research (Bond and Atoum, 2000; Al-Simadi, 2000a), we not only found that participants were better able to detect deception in the outside (Indian) culture than within their own (American) culture, but also, as hypothesized, the deception detection rates were more accurate when Indian participants spoke in their second (English) language than when they spoke in their native (Hindi) language. To gain some more insights about the cues on which the judges relied while making the veracity judgments, we reviewed the responses entered by the

judges for each of the three treatments and compiled them based on the most reliable to least reliable cues to deception (see Table 7).

While judges relied on almost the same cues to identify deception across the three treatment conditions, the ranking of these cues from most reliable to least reliable varied across treatments. For example, the use of incorrect grammar by Indians speaking in English was often linked to deceptive behavior; however, it was not an important cue while judging Americans speaking in English. Surprisingly, the top three cues to deception, regardless of the treatment conditions, were fidgeting, no eye contact, and pauses. While judging Americans, Americans paid more attention to fidgety behavior than pauses; on the other hand, they relied more on pauses than fidgety behavior to detect deception among Indians. Similarly, changes in tone were found to be a more reliable cue while judging Indian participants than while judging Americans.

In sum, though judges relied on same set of cues to detect deception across the three treatments, their reliance on these cues differed when the judgments were made within the same culture and when they were made in the outside culture. Reliance on cues also differed between Indian English and Indian Hindi treatments. For example, stuttering was considered an important indicator of lying behavior for Indians speaking in Hindi; however, it was less often linked to deception for Indians speaking in English.

Table 7. Most reliable to least reliable deceptive cues

<b>American English</b>	<b>Indian English</b>	<b>Indian Hindi</b>
Fidgeting	No Eye Contact	No Eye Contact
No Eye Contact	Pauses/ Hesitant	Pauses/ Hesitant
Pauses/ Hesitant	Fidgeting	Fidgeting
Voice Stuttering	Poor Grammar	Voice Stuttering
Contradicting reply	Tone	Tone
Tone	Repetitive/Wordy reply	Short Answer

Table 7 continued

Rehearsed reply	Contradicting reply	Body Language
Repetitive/Wordy reply	Short Answer	Blinking
Short Answer	Voice Stuttering	Poor Grammar*
Body Language	Body Language	Repetitive/Wordy reply
Poor Grammar	Blinking	Contradicting reply*
Blinking	Biting Lips	Laugh/ Smile
Eye brows movement	Laugh/ Smile	Biting Lips
Laugh/ Smile	The use of “we” as opposed to “I”	Rehearsed reply
The use of “we” as opposed to “I”	Rehearsed reply	Eye brows movement
Biting Lips	Eye brows movement	The use of “we” as opposed to “I”*

\* Only for text-based snippets

### Implications

This study investigated the effects of media, and culture and language on deception detection success. Previous research suggests that approximately one-third of our daily communication involves some form of deception, and the likelihood of correctly identifying deception rarely exceeds 50% (George and Robb, 2008). With the advent of the Internet, individuals nowadays are often involved in communication with people from other cultures. Therefore, it is not only important to understand the process of deception and its detection within the same culture, but also across cultures. Additionally, rapid globalization has led to the increased migration of people around the world such that immigrants, in general, are required to communicate in the language of the foreign country. Our findings suggest that, by examining irregularities in the speaking styles of non-native speakers, native speakers are capable of detecting deception in the outside culture.

Not only it is imperative to understand deception and its detection across cultures, but also, given that CMC-based media have become so ubiquitous that anyone with the Internet

connection and a computer or a smart phone can connect to another person regardless of his or her geographical location, there is a real and practical need to understand the relationship between media and deception detection. Contrary to the common assumption that links media capability to transmit more cues to higher deception detection rates, we found that American judges made more accurate judgments from audio only media, compared to text and video only media. Too few cues in video only and text only media seem to impede judges' ability to correctly identify deception.

Additionally, the investigation of interaction effects between media, and culture and language reveal that, while the judgments made from non-audio only media (audiovisual, text only, and video only) differ considerably across treatment conditions (American English, Indian English, and Indian Hindi), the ones made from the audio only media have a near constant detection success rate. This implies that culture and language of the participants did not significantly impact the detection success of judges in the audio mode.

This study also has implications for research. The literature on deception and its detection has primarily focused on real-time FtF conversations. While the insights from this literature are interesting, due to the pervasiveness of CMC-based media in today's world, future research pertaining to deception and its detection should include CMC. This study is an early attempt in that direction. Furthermore, concerns about the lack of cross-cultural research have often been raised in the MIS discipline (Galliers and Meadows, 2003); thus, by simultaneously looking at the role of several CMC-based media and culture on deception detection, we have taken a small step to address the concerns of parochialism in the field of information systems research.

While there have been several studies (see Table 2) that indicate that beliefs about deception and non-verbal cues to deception are culture-specific, the research investigating the

ability of individuals to detect deception within and between cultures has been scarce (see Table 3). Thus, by comparing the deception detection capabilities of American participants within their own culture and in the outside Indian culture, we have made a significant contribution to the *blue ocean* stream of research that suggests people are better able to detect deception in outside culture compared to their own. Additionally, contrary to the stream of research that treats culture and language as two separate entities, we considered culture and language tightly intertwined with each other. While Bond and Atoum (2000) and Al-Simadi (2000) provided evidence of successful deception across cultures, the impact of language on judgment success was either not found to be significant or not reported in the respective studies. The findings from this study not only suggest that people can detect deception across cultures, but also the likelihood of detection success increases when people make judgments of deception across cultures that share a language.

### **Limitations and future research**

Our study is not without limitations. First, findings from this study largely depend on the experimental task that involved making judgments from the stimulus sets. The stimulus sets were carefully reviewed and edited to ensure an appropriate level of difficulty associated with judging a snippet. We followed the guidelines of Jarvenpaa (1985), who suggest that experimenters must pay considerable attention to the development of the task such that participants do not find it too complex to understand. Second, the American participants, who served as judges, came from the same university, thereby limiting the generalizability of the findings. Third, the study examined differences between only two cultures and two languages; thus, more research is needed to further validate the findings from this study. Future research should consider adding more cultures and including judges from multiple locations. Fourth, to examine the effects of media on

deception detection, we varied media by four different modes: text only, audio only, video only, and audiovisual; however, there are media such as instant messaging (IM) that permit individuals to use emoticons to express their emotions through the use of graphical representations of smiles, winks, and sad and frown faces (Setlock et al., 2004). Additionally, many video-based media (e.g., Google chat, Yahoo messenger) enable participants to simultaneously use text-based chat along with audiovisual or audio only communication. Thus, one interesting avenue for future research would be to examine the relationship between multiple media choices and successful deception detection (Watson-Manheim and Belanger, 2007).

### **Conclusion**

This study investigated the following research questions: How do CMC-based media (audiovisual, audio only, video only, and text only) impact the ability of individuals to detect deception? How do cultural and language differences affect the ability of individuals to detect deception across cultures that share a language and cultures that do not? Our findings indicate that communication media have significant impact on individuals' ability to detect deception. Deception detection was more accurate when individuals made judgments from audio only media compared to when they were asked to make judgments from other media formats. Our study also suggests that culture and language plays an important role in detecting deception. Individuals were better able to detect deception among members of the other cultural group than among the members of their own cultural group. Further, judges were more accurate in detecting lies among non-native English speakers than among native English speakers.

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## CHAPTER 3. THE IMPACT OF ORGANIZATIONAL CULTURE ON AGILE PRACTICES

### Abstract

Much of the existing research on agile software development (ASD) methodologies has primarily focused on proposing the ideal organizational culture for the adoption of agile practices. Given that organizations in different industrial sectors have successfully embraced ASD, this study argues that ASD can be implemented in a range of organizational cultures. Specifically, this study conceptualizes ASD practices into technical and social dimensions and examines how they are impacted by different forms of organizational culture. Another major shortcoming of the extant research on software development methodologies (SDM) is the use of several constructs to measure the benefits of using new SDMs. This study proposes organizational creativity as the main dependent variable to assess the benefits of using ASD. Based on the survey of 225 senior-level agile practitioners, our study found that ASD can be followed in different organizational cultures. We also found support that both technical and agile practices have a positive influence on organizational creativity. Finally, some support was found that organizational culture impacts technical and social dimensions of ASD differently.



## Introduction

Over the years, organizations in all industries have increasingly faced uncertainty in their external environments (Castrogiovanni 2002). Such uncertainty affects customers' needs and expectations thereby causing rapid changes in system requirements during the information systems development (ISD) process (Tiwana 2010; Tiwana and Keil 2009). To cope with environmental uncertainty, organizations must learn to be flexible in their ISD process. The slowness and inflexibility of traditional systems development methodologies (SDMs) to react to the challenges posed by increased environmental uncertainty led to the advent of agile systems development (ASD) (Hong et al. 2011). ASD is characterized by frequent software releases, incremental development cycles, and high levels of collaboration and communication between business people and technical staff.

While research on ASD dates back to the 1990s, it was not until after the publication of the *Agile Manifesto* in 2001 that agile methodologies garnered considerable attention from academics (Abrahamsson et al. 2003; Beck et al. 2001; Dybâ and Dingsoyr 2009; So and Scholl 2009). In the past decade, scholars have furthered this research by focusing on the barriers to ASD. Organizational culture is one such barrier that is often cited as a significant challenge in the adoption of agile practices (Lindvall et al. 2002; Tolfo et al. 2011). Consequently, substantial research on ASD has concentrated on proposing the *ideal* agile culture, which is people-centered and collaborative (Cockburn and Highsmith 2001), democratic (Siakas and Siakas 2007), less formalized and non-hierarchical (Strode et al. 2009), and has an appropriate reward system (Derby 2006).

According to this stream of research, "if the culture is not right, then the organization cannot be agile" (p.203) (Lindvall et al. 2002); however, a recent ethnographic work of Robinson

and Sharp (Robinson and Sharp 2005a) found eXtreme programming, a type of ASD methodology, to be thriving in three fundamentally different organizational settings (a large multi-national bank, a medium-sized software company, and a small start-up). Given that this study involved only three organizations, more research is needed to suggest that there is no one ideal agile culture and agile practices can be embraced in a wide range of organizational cultures.

Apart from erroneously advocating for the optimal agile culture, the existing ASD research has some major shortcomings. First, scholars have primarily focused on the technical side of agile development (Hong et al. 2011; Maruping 2010; Maruping et al. 2009) thereby ignoring the human and social aspects associated with ASD (Agerfalk et al. 2009; Robinson and Sharp 2005b; So and Scholl 2009). We address this shortcoming by conceptualizing agile practices into technical and social dimensions. While engineering-based systems development practices, which are specifically related to software coding, are termed as technical agile practices, social interactions-based management practices are considered social agile practices.

Second, the majority of ASD research has been conducted either using case studies (Cao et al. 2012; Strode et al. 2009; Tolfo and Wazlawick 2008) or ethnographic studies (Robinson and Sharp 2005a). In general, case studies are well-suited for research phenomena that do not have a strong theoretical foundation (Benbasat et al. 1987). With a growing body of literature on ASD, we believe it is time to move away from *how* and *why* forms of research questions, which case studies tend to answer, to *how much* and *what* question forms, which can be efficiently answered by survey methods (Yin 2009). The recent development of survey instruments for assessing agile practices usage demonstrates that scholars now have well-defined dependent and independent variables pertaining to ASD (Maruping et al. 2009; So and Scholl 2009). Another limitation of the extant research is in its choice of the unit of analysis, which has either been a

project or a team (Cao et al. 2012; Chow and Cao 2008; Maruping 2010; Maruping et al. 2009; Robinson and Sharp 2005a; Sharp and Robinson 2008). Recent trends indicate that organizations, such as Deere & Company, Nokia, State Farm Insurance, and ThoughtWorks, have adopted agile practices across their IT departments (agilecout 2011; Lindvall et al. 2004; Thibodeau 2012). Therefore, this study measures all the variables of interest at an IT department-level rather than at a project or a team-level.

In addition to this, a number of constructs have been used in the ISD literature to assess the benefits of adopting new SDMs, yet it remains a challenging task to illustrate their paybacks in terms of productivity and efficiency (Iivari and Huisman 2007). Given that ISD is a highly creative process in which novel ideas, designs, solutions, and artifacts are often produced (Ocker et al. 1995), we propose that the outcome of using a new SDM such as ASD should be measured in terms of creativity (or IT department's creativity). Creativity refers to the novel, valuable, and useful outcome of a complex social system such as the ISD process (Woodman et al. 1993). Since we have conceptualized ASD into technical and social dimensions, this study proposes and investigates the impact of technical and social agile practices on creativity.

Based on the gap and shortcomings discussed, this study addresses the following research questions: 1) What is the extent to which different forms of organizational culture, when applied to IT departments, impact the use of technical and social agile practices? 2) How do technical and social agile practices positively influence an IT department's creativity?

The rest of the paper is structured as follows: We begin with a review of relevant literature pertaining to ASD, organizational culture, and creativity. We then present our hypotheses. Next, we describe our research methods and data analysis. The paper ends with a discussion of findings, followed by implications for practice and research.

## Literature And Hypotheses

### Agile systems development

ASD was specifically devised for today's high velocity markets where speed and agility have become extremely important for organizations (Takeuchi and Nonaka 1986). Unlike traditional *waterfall* SDMs, which are well-suited for stable and predictable markets, ASD facilitates the development and release of software products in Internet time. ASD allows changes in customers' requirements even late in the development cycle and promotes effective communication among individuals involved in the ISD process (Beck et al. 2001). Thus, ASD is radically different from traditional SDMs (see Table 1).

Table 1. ASD versus Traditional Systems Development (Hong et al. 2011)

	<b>Agile Systems Development</b>	<b>Traditional Systems Development</b>
Applicable context	More fluid user requirements	Relatively stable user requirements
Identification of user requirements	Users are constantly solicited for new requirements; emphasis on adaptivity to changing environments	User requirements are typically identified at the start of the development cycle, with emphasis on planning and predicting
Number of development cycles	Many short development cycles	One long development cycle
Development steps with each development cycle	Rigid steps	Rigid steps
Functions available when the systems is first built	System only provides a limited set of functions when first released	System is expected to deliver a full set of functions when first released
Goal in each development cycle	Each release has limited scope, i.e., each release delivers only a few valuable functions	A major release that comes with a complete set of functions

Agile practices were first documented in the *Agile Manifesto* by a group of seventeen accomplished software developers (Beck et al. 2001). The focus of this group was to uncover better ways of developing software. While there is a range of systems development approaches that fall under the umbrella of ASD methodologies, such as test-driven development (TDD), eXtreme programming (XP), feature-driven development (FDD), Scrum, dynamic systems development method (DSDM), and lean programming, they all adhere to the four core values: *(1) individuals and interactions over processes and tools, (2) working software over comprehensive documentation, (3) customer collaboration over contract negotiation, and (4) responding to change over following a plan* (Beck et al. 2001). Of the several ASD methodologies, XP has so far been the most widely-adopted (Cao et al. 2009; Maruping 2010; Maruping et al. 2009). XP is an engineering methodology that provides strong guidelines for developing high quality software (Mar and Schwaber 2002). It mainly focusses on the technical side of ISD and thus offers limited insights into the social side of ISD, causing a disconnect between management and developers (Mar and Schwaber 2002). To bridge this disconnect, XP is often complemented with Scrum, a social-engineering based agile methodology (Schwaber and Beedle 2002).

Although both XP and Scrum prescribe the same core values of the *Agile Manifesto*, XP practices, such as pair-programming, unit testing, continuous integration, refactoring, collective ownership, and coding standards (see Table 2 for definitions), are targeted towards the development of quality software while keeping it flexible for incorporating future changes that may arise due to changing customers' needs (Beck and Andres 2004). Scrum, on the other hand, facilitates frequent interactions and effective collaboration among the customer, management, and developers (Hummel 2013). Scrum mainly consists of three practices: daily standup,

retrospectives, and access to the product owner. Daily standups enable knowledge sharing and dense communication between technical and management staff. Retrospective meetings identify the challenges and issues faced in the past development cycle and how they should be effectively dealt with in future (Sutherland and Schwaber 2007). Additionally, Scrum has an important role - the product owner - the person who represents the customer and, in some cases, can be an actual customer.

While both XP and Scrum are agile methodologies, the former is engineering-based or technical in nature, while the latter is more socially-oriented. In the past decade, organizations in different industries have successfully adopted technical and social agile practices across their IT departments; however, organizations tend to adopt the practices that best suit their ISD needs (Fitzgerald et al. 2006; Lindvall et al. 2004; Sutherland and Schwaber 2007). For example, Intel in Shannon, Ireland employs a mix of technical (XP) and social (Scrum) practices in their ISD (Fitzgerald et al. 2006). Consistent with this and given that technical practices are often complemented with social practices (Schwaber and Beedle 2002), this study focuses on a mix of six widely-used technical (XP) (Maruping et al. 2009) and three widely-adopted social (Scrum) agile practices (So and Scholl 2009) (see Table 2).

Table 2. Description of Agile Software Development Practices

<b>Dimension</b>	<b>Agile Practice</b>	<b>Description</b>	<b>Reference</b>
Technical	Pair-programming	All production code is written with two programmers at one machine (p.48).	(Beck 2006)
Technical	Unit testing	Programmers continually write unit tests, which must run flawlessly for development to continue (p.48).	(Beck 2006)
Technical	Continuous Integration	Integrate and build the system many times a day, every time a task is completed (p.48).	(Beck 2006)
Technical	Refactoring	The design of the system is evolved through transformations of the existing design that keep all the tests running (p.71).	(Beck 1999)
Technical	Collective Ownership	Every programmer improves any code anywhere in the system at any time if they see the opportunity (p.71).	(Beck 1999)
Technical	Coding Standards	Programmers write all code in accordance with rules emphasizing communication through the code (p.48).	(Beck 2006)
Social	Customer/Product Owner Role	The person responsible for articulating the product vision. This person actively works with other members to clear any issue pertaining to product features/requirements during systems development. He/she is the voice of the customer/end-user.	(Sutherland and Schwaber 2007)
Social	Daily Standup	A short meeting (time-boxed to 15 minutes) that takes place every day at the same time in which individuals give a daily status of their assigned tasks.	(Sutherland and Schwaber 2007)
Social	Retrospectives	A meeting that is used to discuss questions such as "what went wrong" and "what went well" in the past development cycle. It helps identify "what could be improved" in future development cycles.	(Sutherland and Schwaber 2007)

## **Organizational culture**

Culture is a major focus of research in organization behavior-related studies and is often considered a major barrier to “determining patterns of IT development, adoption, use, and outcomes” (p.381) (Hatch 2012; Iivari and Iivari 2011; Leidner and Kayworth 2006). A substantial amount of research calls culture a complex construct since it encompasses nearly all areas of an organization (Iivari and Huisman 2007). Further, organizational culture has been defined in numerous ways. While House et al. (2002) assert that organizational culture reflects commonly used terminology, shared organizational values, and organizational history, Dowling (1993) calls it a glue, which keeps an organization together.

In addition to its several definitions, organizational culture is considered to exist at many levels. Schein (1990b) defines organizational culture at three levels: artifacts, espoused values, and basic underlying assumptions. While artifacts exist at the surface level and thus represent tangible and visible aspects of organizational culture such as the physical layout and the dress code, assumptions reflect the hidden characteristics of organizational culture such as employees' perceptions, feelings, and behaviors (Schein 1990b). Espoused values lie between artifacts and assumptions and they describe organizational norms, ideologies, and philosophies through which employees perform their day-to-day tasks.

This study defines organizational culture in terms of values because of the challenges associated with the measurement of artifacts and assumptions. Assumptions are deep-rooted in an organization's history, implying they can only be studied through intensive observations (Schein 1990b). Artifacts, though highly visible, cannot be interpreted correctly without decoding the underlying assumptions (Schein 1990b). Thus, it is not surprising that the two widely-cited frameworks of culture – Hofstede's (1980) and Quinn and Rohrbaugh's (1983) -



are both based on the values' perspective. Moreover, Schein (1990a) indicates that espoused values, in comparison with artifacts and assumptions, can be easily measured via surveys. While Hofstede's framework is based on national culture, Quinn and Rohrbaugh's competing values framework (CVF) focuses on organizational culture. Since we are primarily interested in organizational culture, when applied to IT departments, this study uses CVF. CVF is a well-accepted framework of organizational culture and has been actively used in the studies of management information systems, especially in the ones pertaining to ISD (Huang et al. 2003; Iivari and Huisman 2007; Iivari and Iivari 2011; Ngwenyama and Nielsen 2003; Strode et al. 2009).

### **Organizational culture and ASD**

CVF is based on the two pairs of competing values (or dimensions): (1) internal focus versus external focus and (2) flexibility versus stability. While one describes whether an organization values the welfare of its employees (i.e., internal focus) versus the welfare of the organization itself (i.e., external focus) (Quinn and Rohrbaugh 1981; Quinn and Rohrbaugh 1983), the other differentiates organizations based on the degree of structure (i.e., flexibility versus stability) (Quinn and Rohrbaugh 1981; Quinn and Rohrbaugh 1983). We first discuss the differences between internally-focused and externally-focused organizational cultures.

Internally-focused organizations tend to establish harmony among employees by developing a family-like culture, while externally-focused organizations stress continuous competition with rival firms (Denison and Spreitzer 1991). Simply put, internal focus describes the extent to which an organization values its employees' personal feelings, likes and dislikes, whereas external focus reflects an organization's disposition to minimizing individuality and

emphasizing growth of the organization as a whole (Quinn and Rohrbaugh 1981; Quinn and Rohrbaugh 1983). According to Cameron (2006), the basic difference between the competing ends of this dimension lies in terms of how different organizations pursue value creation.

Externally-focused organizations tend to be highly competitive because they are constantly evaluating and identifying future trends in and out of their principal industry (Cameron 2006).

These organizations closely follow the activities of their competitors and strive hard to outperform them.

Given that technical agile practices enable organizations to quickly respond to the changes due to environmental uncertainty, a culture that values competitiveness and experimentation is likely to promote technical practices. Technical practices advocate that all software code should be developed by a pair of software developers per some agreed-upon standards, resulting in the creation of best technical designs and architects (Fowler and Highsmith 2001). These excellent designs and other technical artifacts make the ISD process highly flexible, especially when new requirements are proposed either due to changing customers' needs or evolving priorities. An organization that follows technical agile practices is relatively well-equipped to respond to the alterations caused in the external environment. Based on this, we suggest:

**H1: Externally-focused organizational culture will have a positive impact on the use of technical agile practices.**

While technical practices allow organizations to be competitive by allowing flexibility in the ISD process, internally-focused organizations are more concerned about creating value by enhancing their internal competencies rather than following the activities of their rivals (p.9) (Cameron 2006). Thus, it is likely that these organizations, due to their internal focus, may not

perceive value in adopting technical practices. Further, employees in these organizations are more comfortable performing familiar tasks rather than trying new activities or processes (Cameron 2006). Given that technical practices, such as pair-programming, refactoring, continuous integrations, collective ownership, and unit testing, require significant shift from the values prescribed by the traditional SDMs, employees in internally-focused organizations might be less willing to alter their existing ISD process. Therefore:

**H2: Internally-focused organizational culture will have a negative impact on the use of technical agile practices.**

The second pair of competing values, consisting of flexibility and stability, differentiates organizations based on their structure (Quinn and Rohrbaugh 1983). While stability implies controlled or bureaucratic organizational structure, flexibility reflects an organization's ability to overcome organizational inertia by continuously changing and adapting. This pair makes a distinction between organic and mechanistic organizations (Burns and Stalker 1961; Denison and Spreitzer 1991). More than five decades earlier, Burns and Stalker (1961) suggested that organizations adopt organic structure by removing hierarchical barriers and providing a workplace environment in which individuals, regardless of their job titles, are free to interact and express their views with each other.

Communication patterns in organic organizations are similar to friendly discussions rather than formal orders (Lawrence and Lorsch 1967). As tasks become more complex, the need for increased levels of communication and member participation becomes critical for an organization to survive (Lawrence and Lorsch 1967). ISD is one such complex process that

requires participation of several individuals and effective communication among them (Tiwana and McLean 2003). Social agile practices, such as daily standups, retrospective meetings, and access to the product owner, remove communication barriers by allowing everyday interactions between technical and management staff. These social interactions enable individuals to clarify system requirements, share their expertise, and update each other about the overall systems development progress. Given that flexible culture encourages equal member participation and face-to-face interactions, we propose:

**H3: Flexible organizational culture will have a positive impact on the use of social agile practices.**

Organizations that are conducive to stability tend to structure (or control) their communication patterns. These organizations follow authoritative top-down leadership style in which employees are expected to adhere to the instructions of their superiors. Since member participation and employee interactions are essential for the ISD process when social agile practices are followed, a controlled organizational culture will likely to discourage their usage. Daily standup, retrospective meetings and access to the product owner provide several opportunities to individuals involved in the ISD process to interact on daily basis. Thus, a culture that promotes vertical communication rather than lateral communication is less likely to use social practices.

**H4: Stable organizational culture will have a negative impact on the use of social agile practices.**

We have thus far specifically focused on the two competing dimensions (internal focus versus external focus and flexibility versus stability) of organizational culture; however, the intersection between these two pairs generates four different forms of organizational culture (see

Figure 1). Per CVF, quadrant I represents group culture, which is flexible and internally-focused. A group culture-oriented organization is concerned about its employees and promotes openness, teamwork, consensus, and participation (Cameron and Quinn 2011). Quadrant II signifies developmental culture, which is characterized by an external focus and a flexible structure. This culture is forward-looking and places a high premium on expansion and exploring new growth opportunities (Denison and Spreitzer 1991). Quadrant III shows rational culture, which lies at the intersection of external focus and stability. This form of organizational culture stresses performance, goal accomplishment, efficiency, and achievement (Cameron and Quinn 2011). Quadrant IV denotes hierarchical culture, which emphasizes uniformity and stability in the internal environment of an organization.

The advantage of using CVF is that it does not only allow us to focus on the two widely-discussed dimensions of organizational culture, but also on the intersection between the two. While we initially proposed our hypotheses (H1-H4) in terms of internal focus (versus external focus) and flexible (versus stable) values, these hypotheses can be further expressed in terms of group culture (quadrant I), developmental culture (quadrant II), rational culture (quadrant III), and hierarchical culture (quadrant IV) (see Figure 1 and Table 3).

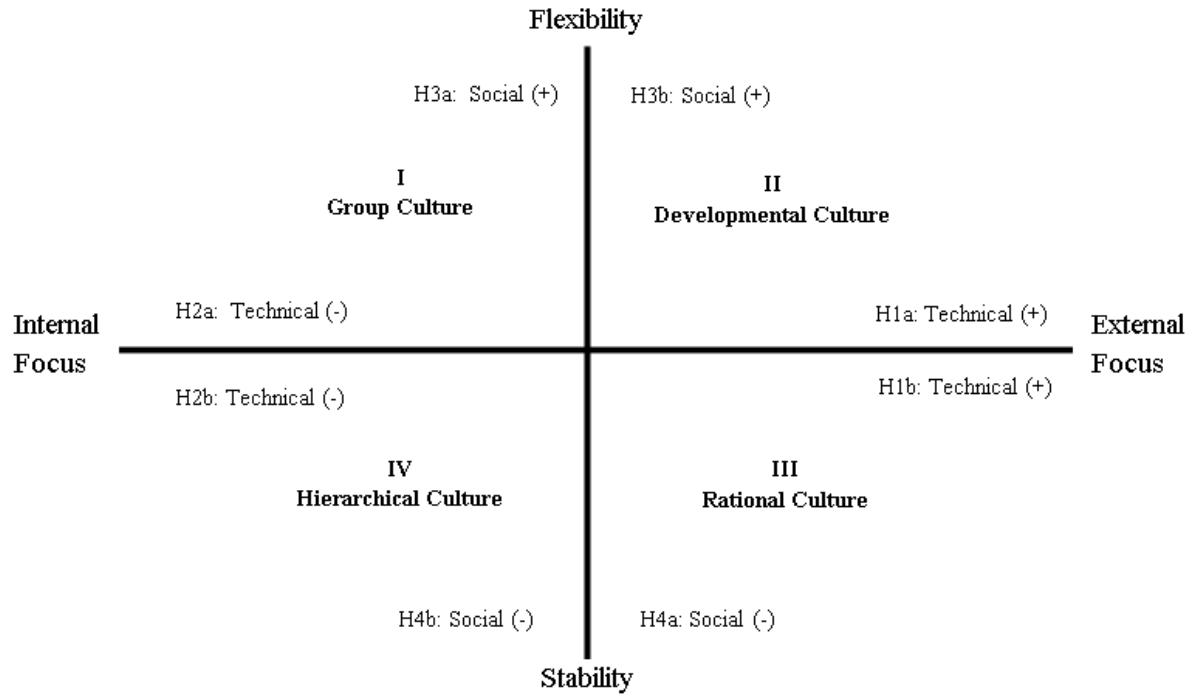


Figure 1. Relationship between culture and agile practices

Table 3. Reframed hypotheses in terms of four cultural forms

<b>Initial Hypotheses</b>	<b>Reframed Hypotheses</b>
<b>H1:</b> Externally-focused organizational culture will have a positive impact on the use of technical agile practices.	<b>H1a:</b> Developmental culture will have a positive impact on the use of technical agile practices.
	<b>H1b:</b> Rational culture will have a positive impact on the use of technical agile practices.
<b>H2:</b> Internally-focused organizational culture will have a negative impact on the use of technical agile practices.	<b>H2a:</b> Group culture will have a negative impact on the use of technical agile practices.
	<b>H2b:</b> Hierarchical culture will have a negative impact on the use of technical agile practices.
<b>H3:</b> Flexible organizational culture will have a positive impact on the use of social agile practices.	<b>H3a:</b> Group culture will have a positive impact on the use of social agile practices.

	<b>H3b:</b> Developmental culture will have a positive impact on the use of social agile practices.
<b>H4:</b> Stable organizational culture will have a negative impact on the use of social agile practices.	<b>H4a:</b> Rational culture will have a negative impact on the use of social agile practices.
	<b>H4b:</b> Hierarchical culture will have a negative impact on the use of social agile practices.

### Organizational creativity

Organizational creativity is defined as “the creation of valuable and useful products, services, ideas, or procedures by individuals working together in complex social settings” (p.293) (Woodman et al. 1993). A substantial amount of literature suggests that creativity is closely related to innovation; however, there is a subtle difference between the two in an organizational sense (Woodman et al. 1993; Zhou and Shalley 2007). While creativity refers to the process of producing new ideas or developing efficient ways of doing a particular organizational task, innovation refers to the successful introduction of creative ideas (Gurteen 1998; Rogers 1998; Woodman et al. 1993). Thus, creativity is necessary, but not sufficient for guaranteeing innovation (Amabile 1996).

The process of innovation does not pertain to where the creative ideas were first invented; instead, the main purpose behind their implementation is to increase organizational performance (Rogers 1998). Organizational creativity is an outcome of doing something unique that has not been done earlier (Amabile 1996). Moreover, an idea can be termed creative only after it was evaluated by experts (Amabile 1996). For example, poets are capable of assessing the degree to which poems are creative, while graduate-level business students can evaluate the creativity of solutions to business problems (Amabile 1996).

Creative ideas are often generated during the development of complex systems (e.g., aircrafts, autos, and computers) (Kazanjian et al. 2000). It is the uncertainty surrounding the final outcome (or deliverable) that makes the development of these systems highly complex (Kazanjian et al. 2000). In this study, we are interested in the creative outcome of one such complex process - the ISD process. ISD is considered complex because it not only converts abstract ideas into tangible features, but it also requires several individuals to work together and share their technical know-how, skills, and insights with each other (Ocker et al. 1995; Tiwana and McLean 2003).

As organizations continue to face uncertainty in their external environments, they are under constant pressure to develop information systems for novel business requirements and unexplored problem domains (Tiwana and McLean 2003). ASD enables organizations to address the challenges posed by turbulent environments and be creative at the same time (Tolfo et al. 2011). The use of simpler non-rigid technical practices over complicated traditional processes increases the creativity of the ISD process (Fowler and Highsmith 2001). Technical agile practices, such as pair-programming, continuous integration, refactoring, unit testing, collective ownership, and coding standards, facilitate the development of high quality software, leading to the creation of novel, valuable, and useful technical artifacts (Beck and Andres 2004; Fowler and Highsmith 2001). These creative technological artifacts make the ISD process flexible such that unplanned requests from the customer can be efficiently addressed without impacting the development of the overall system. Based on this, we propose:

**H5: Technical agile practices usage will have a positive impact on the creativity of an IT department.**



One of the primary criticisms of the traditional SDMs is minimal or no feedback between the phases of a software development life cycle (SDLC). The traditional software development lifecycle was suggested in terms of multiple phases where a project starts in the planning phase and then subsequently moves into analysis, design, implementation, and maintenance phases. While the original developer of the traditional SDLC, W.W. Royce, highlighted the need for continuous feedback between these phases, organizations largely ignored the feedback part in the ISD process (Hoffer 1999). As a consequence, communication between individuals, especially those in different phases, is limited, resulting in unequal dissemination of information. Another criticism of traditional methodologies is the near absence of customer feedback in the ISD process (Hoffer 1999), resulting in a disconnect between what is being developed and what the customer want.

Social agile practices increase everyday communication between the customer, management, and technical staff. Social practices, such as daily standups and retrospective meetings, foster face-to-face and frequent employee interactions thereby allowing individuals to update each other about the overall progress of the systems development. Additionally, availability of the product owner bridges the disconnect between customers' needs and developers' understanding of the customers' expectations. Given that social agile practices foster organizational communication, and given that creativity is reduced when too many restrictions are placed on organizational communication [72], we suggest:

**H6: Social agile practices usage will have a positive impact on the creativity of an IT department.**

## Methodology

To test our hypotheses, we created a survey in Qualtrics. The survey was sent via email to 950 participants in the United States, who were randomly selected from an online LinkedIn community of over 12,000 senior-level agile practitioners. The analysis was conducted at the IT department-level. In total, 225 responses (23.6 percent response rate) were received (see Table 4 for sample characteristics). Respondents represented a variety of industries (e.g., computers, financial services, internet, communications and utilities) and their job titles included technology manager, project manager, program manager, product manager, business analyst, and agile consultant.

Table 4. Sample Characteristics (N = 225)

<b>Industries</b>	
Computers	31.6%
Finance, Insurance, & Real Estate Services	21.8%
Internet	8.9%
Communications, Utilities	6.2%
Others	4.0%
<b>Total IS Experience</b>	27.6%
Less than 5 years	7.6%
5 to 10 years	20.4%
More than 10 years	72.0%
<b>Total Agile Experience</b>	
Less than 5 years	43.1%
5 to 10 years	40.0%
More than 10 years	16.9%
<b># of Employees in the Organization</b>	
Fewer than 1,000	44.4%
1,000 to 10,000	26.3%
More than 10,000	29.3%
<b># of Employees in the IT department</b>	
Fewer than 100	61.3%
100 to 500	21.8%
More than 500	16.9%

## Construct measures

Measures were drawn from the literature on ASD and organizational behavior. Six technical agile practices (pair-programming, unit testing, continuous integration, refactoring, and collective ownership) and three social agile practices (daily stand-up, access to customer/product owner, and retrospectives) were measured using the scales proposed by Maruping et al. (2009) and So and Scholl (2009) respectively. The scores for each technical and social practice was computed by averaging their indicator items to form the higher-level constructs of technical agile practices and social agile practices. Before computing these scores, a reliability analysis was conducted and the items with poor reliabilities were dropped such that scales for each agile practice had a Cronbach  $\alpha$  of at least 0.70 (see APPENDIX A for list of items and reliabilities). Creativity was measured using five items proposed by Lee and Choi (2003), while the four cultural constructs were measured using the scales suggested by Iivari and Huisman (2007) (see APPENDIX B for the measures of creativity and culture). Since we had more than one response from some organizations, we used the organization name as a control variable.

We checked for nonresponse bias using Armstrong and Overton's (1977) method of comparing the responses of early respondents with late respondents on all variables. The analysis revealed no statistically significant differences: group culture ( $t = 0.855$ , ns), developmental culture ( $t = 0.604$ , ns), rational culture ( $t = 0.982$ , ns), hierarchical culture ( $t = 0.416$ , ns), refactoring ( $t = 0.234$ , ns), continuous integration ( $t = 0.55$ , ns), unit testing ( $t = 0.055$ , ns), pair-programming ( $t = 1.489$ , ns), retrospectives ( $t = 0.183$ , ns), stand up/daily scrum ( $t = 0.186$ , ns), access to the product owner ( $t = 0.884$ , ns), and creativity ( $t = 0.37$ , ns). In addition to this, Harman's single-factor test was performed to check whether common method variance was a major concern (Podsakoff and Organ 1986). All seven variables were entered into an exploratory

factor analysis using principal components analysis. The number of factors was then determined by examining the unrotated factor solution. A single factor should account for the majority of covariance in the latent variables in case of a significant common method variance (Podsakoff and Organ 1986). The analysis revealed seven factors and no general factor was apparent.

### **Data analysis**

We used SmartPLS (version 2.0.M3) to assess the measurement model and test the proposed hypotheses. Several measurement models were evaluated and items that had outer loadings below 0.5 were dropped from the analysis (Hair Jr et al. 2013). While hierarchical culture was reduced to two items, all items were retained for group culture, rational culture, developmental culture, and creativity (see Table 5 for internal consistency reliabilities (ICR) and average variance extracted (AVE)). While averaged scores of daily stand-ups, retrospectives, and access to the product owner had outer loadings above 0.5 on the social agile practices construct, the technical agile practices construct was reduced to 5-items (pair-programming, continuous integration, coding standards, refactoring, and unit testing) because collective ownership was dropped due to its low outer loading.

We then assessed the reliabilities, discriminant validity, and convergent validity. According to Hair and colleagues' (2013), internal consistency reliabilities (ICR) between 0.70 and 0.90 are considered satisfactory. Further, an average variance extracted (AVE) value of more than 0.50 establishes convergent validity of a latent construct (Hair Jr et al. 2013). Discriminant validity was assessed using the Fornell-Larcker criterion, which suggests that the square root of the AVEs of each latent variable should be greater than its correlation with any other construct (Fornell and Larcker 1981). The values reported in Table 5 demonstrate sufficient ICRs (all

values > 0.70), convergent validity (all AVEs > 0.50), and discriminant validity (i.e., the diagonal elements are greater than the construct's correlations with any other constructs).

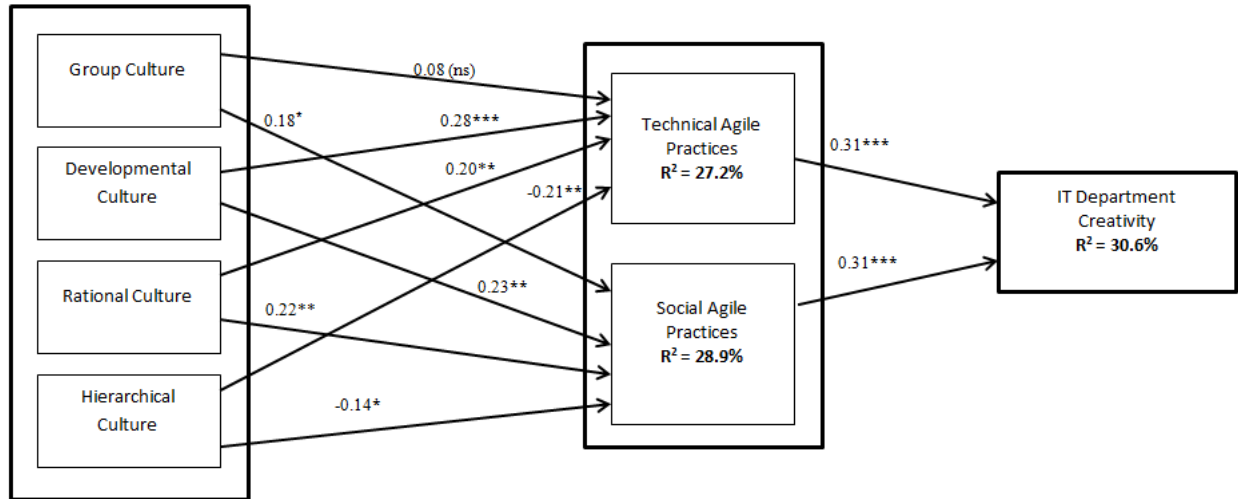
Discriminant validity was further assessed by examining items' cross loadings, which were all found to be smaller than their factor loadings (Hair Jr et al. 2013).

Table 5. Reliabilities and Correlations

Construct	ICR	AVE	Correlation of Constructs*							
Developmental Culture	0.84	0.639	<b>0.800</b>							
Group Culture	0.829	0.621	0.654	<b>0.788</b>						
Hierarchical Culture	0.860	0.757	-0.190	-0.143	<b>0.873</b>					
Rational Culture	0.794	0.531	0.468	0.360	0.236	<b>0.702</b>				
Social Practices	0.835	0.628	0.480	0.432	-0.157	0.358	<b>0.793</b>			
Technical Practices	0.839	0.515	0.468	0.368	-0.230	0.310	0.585	<b>0.718</b>		
Creativity	0.937	0.748	0.640	0.398	-0.151	0.323	0.493	0.490	<b>0.865</b>	

\*The square root of AVEs appear on the diagonals in bold in the correlation of constructs matrix

We then performed the significance testing of the proposed hypotheses using a bootstrapping procedure with 300 resamples. One-tailed  $t$  tests were used because of the directional hypotheses. Organization name, the control variable, accounted for less than 0.011 percent ( $\beta = -0.043$ ,  $t = 0.66$ , ns), implying no statistically significant impact on creativity. The model (see Figure 2) accounted for 30.6 percent of the variance in the IT department's creativity, and 27.2 percent and 28.9 percent of the variance in technical agile and social agile practices respectively.



Notes: N= 225; ns (not significant); \* p < 0.05; \*\* p < 0.01; \*\*\* p < 0.001.

Figure 2. Results

The relationship between developmental culture and technical agile practices was significant (H1a:  $\beta = 0.28$ ,  $t = 4.12$ ,  $p < 0.001$ ). Similarly, rational culture had a positive influence on technical agile practices (H1b:  $\beta = 0.20$ ,  $t = 2.69$ ,  $p < 0.01$ ). Hierarchical culture was negatively related to technical agile practices (H2b:  $\beta = -0.21$ ,  $t = 3.44$ ,  $p < 0.01$ ). H2a, which proposed a negative relationship between group culture and technical practices was not supported ( $\beta = 0.08$ , ns). H3a and H3b, which proposed a positive relationship between group culture and social agile practices ( $\beta = 0.18$ ,  $t = 1.95$ ,  $p < 0.05$ ) and between developmental culture and social agile practices ( $\beta = 0.23$ ,  $t = 2.62$ ,  $p < 0.01$ ) respectively, were both supported. As proposed, hierarchical culture had a negative impact on social agile practices thereby supporting H4b ( $\beta = -0.14$ ,  $t = 2.10$ ,  $p < 0.05$ ). This study also proposed that rational culture would be negatively related to social agile practices (H4a); however, the results indicated the opposite such that rational culture was found to have a positive influence on social agile practices ( $\beta = 0.22$ ,  $t =$

3.10,  $p < 0.01$ ). Finally, the paths between technical practices and creativity (H5:  $\beta = 0.31$ ,  $t = 5.19$ ,  $p < 0.001$ ), and social practices and creativity (H6:  $\beta = 0.31$ ,  $t = 4.55$ ,  $p < 0.001$ ) were both significant.

Table 6. Summary of Results

Hypotheses		Results	Significance
H1a	Developmental culture will have a positive impact on the use of technical agile practices.	Supported	$\beta = 0.28^{***}$ ( $t = 4.12$ )
H1b	Rational culture will have a positive impact on the use of technical agile practices.	Supported	$\beta = 0.20^{**}$ ( $t = 2.69$ )
H2a	Group culture will have a negative impact on the use of technical agile practices.	Not Supported	$\beta = 0.08$ (ns)
H2b	Hierarchical culture will have a negative impact on the use of technical agile practices.	Supported	$\beta = -0.21^{**}$ ( $t = 3.44$ )
H3a	Group culture will have a positive impact on the use of social agile practices.	Supported	$\beta = 0.18^*$ ( $t = 1.95$ )
H3b	Developmental culture will have a positive impact on the use of social agile practices.	Supported	$\beta = 0.23^{**}$ ( $t = 2.62$ )
H4a	Rational culture will have a negative impact on the use of social agile practices.	Not Supported	$\beta = 0.22^{**}$ ( $t = 3.10$ )
H4b	Hierarchical culture will have a negative impact on the use of social agile practices.	Supported	$\beta = -0.14^*$ ( $t = 2.10$ )
H5	Technical agile practices usage will have a positive impact on the creativity of an IT department.	Supported	$\beta = 0.31^{***}$ ( $t = 5.19$ )
H6	Social agile practices usage will have a positive impact on the creativity of an IT department.	Supported	$\beta = 0.31^{***}$ ( $t = 4.55$ )

Notes: ns (not significant); \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .

## Discussion

Past ASD research has erroneously concentrated on proposing the ideal agile culture. This stream of research has also ignored the social dimension of ASD and instead focused on technical agile practices. Moreover, since organizations tend to adopt new SDMs across their IT departments, this study argued that the creative outcome of using agile practices should be measured at the IT department-level. The results yielded interesting insights, indicating that agile practices can be successfully followed in a range of organizational cultures. We also found partial support that culture might influence social and technical dimensions of ASD differently. Additionally, both technical and social agile practices were found to positively affect the creativity of the IT department.

Eight of the ten hypotheses were supported (see Table 6). Developmental culture had a positive impact on the use of technical (H1a) and social practices (H3b). As discussed previously, developmental culture lies at the intersection of external focus and flexibility. While external focus is likely to encourage the use of engineering-based technical practices, flexibility in organizational structure stimulates employee interactions and member participation thereby supporting the use of social practices in systems development.

We predicted that hierarchical culture would be negatively related to both technical (H2b) and social practices (H4b). Both of these hypotheses were supported. Hierarchical culture tends to be internally-focused and highly formalized. This culture is more concerned about the internal functioning of the organization and is less concerned about the activities of rival firms. As a consequence, hierarchical culture is less likely to promote technical practices, which allow organizations to stay ahead of the competition. Moreover, since these organizations tend to have



a stable structure such that the leadership style is top-down and communication is controlled, the likelihood of using social agile practices in these organizations is low.

We argued for a positive relationship between rational culture and technical practices (H1b), and for a negative relationship between rational culture and social practices (H4a). Rational culture reflects authoritative and externally-focused values. Consistent with externally-focused developmental culture, rational culture had a positive influence on technical practices. Given that rational culture, like hierarchical culture, promotes stable and formal organizational structure, we proposed a negative relationship between rational culture and social practices. Surprisingly, the results indicated a positive relationship between the two. This could be due to the interaction between authoritative and externally-focused values of rational culture, which makes this cultural form less authoritative as opposed to hierarchical culture. Further, though rational culture endorses stable organizational structure, Iivari and Huisman (2007) argue that, due to their external focus, rational organizations are quick to implement new SDMs if their benefits are apparent. Given that social agile practices, unlike traditional SDMs, allow everyday communication between business and technical staff, the benefits of using these practices become apparent relatively quickly. Thus, it is possible that, despite controlled organizational structure, rational organizations may still encourage social agile practices.

We proposed that group culture, which lies at the intersection of internal focus and flexibility, would have a negative influence on technical practices (H2a), but would positively relate to social practices (H3a). Similar to internally-focused hierarchical culture, we expected a negative relationship between group culture and technical practices; however, this relationship was not supported. We had argued that internally-focused organizations are less likely to follow technical agile practices since these organizations are more concerned about the internal

functioning of the organization rather than gaining competitive advantage over rival firms. We further argued that technical agile practices are significantly different than the values suggested by traditional SDMs and thus require considerable learning effort of employees, who may find it difficult to adapt to non-traditional SDMs. Given that group culture, though internally-focused, tends to have flexible organizational structure, we believe that the interaction between internal focus and flexible values of group culture might have resulted in the lack of support for H2a. We did, however, find support for H3a, implying that flexible group culture is likely to endorse social practices.

Our final set of hypotheses predicted that technical practices (H5) and social practices (H6) would increase an IT department's creativity. Results provided support for both. Technical agile practices enable organizations to creatively develop information systems for novel and unexplored business problems. Specifically, technical practices, such as advocating the use of two developers to write all code, providing immediate feedback in case there are any integration issues due to newly developed code, and enforcing the use of agreed-upon coding standards, lead to generation of novel and valuable technical artifacts.. Social practices, on the other hand, facilitate information sharing and effective communication between business people and technical staff. This helps in clarifying doubts pertaining to system requirements, discussing progress, resolving impediments, and reevaluating priorities. Simply put, information is not controlled and is readily available to everyone involved in the ISD process. Since creativity is hampered when information is controlled (Woodman et al. 1993), it stands to reason that the use of social practices would have a positive impact on creativity.

### **Implications for research and practice**

The present study yields some interesting insights for practice. Contrary to existing research, we found that there is no ideal agile culture and, except for hierarchical culture, ASD can be successfully followed in a range of organizational cultures. The only cultural form which IT managers interested in implementing ASD should be wary of is hierarchical culture. There was partial support to suggest that cultural forms impact social and technical dimensions of ASD differently. While group, developmental, and rational forms of culture were found to encourage social agile practices in ISD, only developmental and rational culture had a significant positive relationship with technical practices. This suggests that IT managers of group culture-oriented organizations should invest more in social practices rather than in technical practices.

The findings of this study also provide valuable contributions to the growing body of research on ASD. Compared to prior research that has largely focused on case or ethnographic studies, this study adopted a survey method, thereby making the findings more generalizable across organizations. The unit of the analysis in this study was the IT department instead of a team or a project. We argued that since organizations are more likely to introduce agile practices across their IT departments, it was reasonable to assess the impact of using these practices at the IT department-level. While several constructs have been used in the ISD literature to measure the outcome of using a new SDM, this study employed creativity as the main dependent variable. While the importance of creativity in systems development is well-recognized in practice, it is surprising that the construct of creativity has received scant attention in the ISD literature (Tiwana and McLean 2003). By focusing on creativity as the outcome of using agile practices, this study extends our understanding about the scarcely studied concept of creativity in the management information systems literature (Tiwana and McLean 2003).

### **Limitations and future research**

While the findings of this study are interesting and informative, the study is not without limitations. First, the sample consisted of only US-based firms. Given that there are substantial management differences between American and non-American firms (Hofstede 1993), caution must be exercised while making generalizations of the findings from this study to non US-based firms. Second, although Harman's single-factor test did not provide any evidence of mono-method bias, it should be repeated that all data in this study were collected using self-reported survey-based measures. Third, this study used a single respondent, a senior-level agile practitioner, per organization (or IT department). Multiple respondents from the same IT department (or organization) would have provided stronger evidence for the findings.

We believe that there are a number of avenues for future research. Given that this study primarily consisted of US-based organizations, more research is needed to conclude whether the findings from this study will hold in non-American organizations. Thus, the present study can be extended by including a broader sample of organizations from different countries. Additionally, this study did not specifically make any distinction between in-house systems development and outsourced systems development processes; therefore, another interesting avenue for future research is to explore how different cultural forms affect the use of agile practices during in-house systems development as opposed to outsourced systems development.

### **Conclusion**

This study investigated the interplay of organizational culture, when applied to IT departments, and the use of agile practices and an IT department's creativity. The results from this study calls for a major shift from the prevalent view in the literature that has argued for the

ideal agile culture. Based on the survey of 225 experienced agile practitioners, this study indicates that agile practices can be effectively used in a variety of organizational cultures. However, it is important that organizations understand the differences between technical and social aspects of ASD since not all forms of organizational culture impact the technical and social sides of ASD in the same manner. Further, while there are considerable differences between engineering-based technical and management-based social agile practices, both of these practices enhance creativity of the IT departments. Lastly, our results suggest interesting directions for future research on ASD. We also hope that future studies will use more of non-case methods and will include a broader sample of organizations from multiple nations so that the findings can be generalized across organizations in different countries.

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## APPENDIX A

## MEASURES OF TECHNICAL AND SOCIAL AGILE PRACTICES

**Continuous Integration** (Cronbach  $\alpha = 0.77$ ) (Source: Maruping et al. (2009))

		Mean	S.D.
CI1	We integrate newly coded units of software with existing code.	6.12	0.96
CI2	We combine new code with existing code on a continual basis.	6.10	1.06

**Refactoring** (Cronbach  $\alpha = 0.87$ ) (Source: Maruping et al. (2009))

REF1	Where necessary, we try to simplify existing code without changing its functionality.	5.66	1.22
REF2	We periodically identify and eliminate redundancies in the software code	5.43	1.40
REF3	We periodically simplify existing code	5.11	1.51

**Unit Testing** (Cronbach  $\alpha = 0.85$ ) (Source: Maruping et al. (2009))

UT1	We run unit tests on newly coded modules until they run flawlessly.	5.41	1.48
UT2	We actively engage in unit testing.	5.79	1.33
UT3*	To what extent are unit tests run by the members in this department?	5.58	1.45

**Collective Ownership** (Cronbach  $\alpha = 0.70$ ) (Source: Maruping et al. (2009))

CO1	Anyone can change existing code at any time.	4.62	2.03
CO2	If anyone wants to change a piece of code, they need the permission of the individual(s) that coded it.	2.44	1.52
CO3	We are comfortable changing any part of the existing code at any time.	4.50	1.69

**Coding Standards** (Cronbach  $\alpha = 0.84$ ) (Source: Maruping et al. (2009))

CS1	We have a set of agreed upon coding standards in this team.	5.39	1.37
CS2	We have a shared understanding of how code is to be written.	5.43	1.29

**Pair Programming** (Cronbach  $\alpha = 0.94$ ) (Source: Maruping et al. (2009))

PP1*	How often is pair programming used in this department?	3.74	1.79
PP2	We do our software development using pairs of developers	4.35	1.97
PP3*	To what extent is programming carried out by pairs of developers in this department	3.84	1.79

**Daily Standup** (Cronbach  $\alpha = 0.73$ ) (Source: So and Scholl (2009))

		<u>Mean</u>	<u>S.D.</u>
DS1	Stand up meetings are extremely short (max. 15 minutes).	5.67	1.51
DS2	Stand up meetings are to the point, focusing only on what has been done and needed to be done on that day.	5.40	1.42
DS3	All relevant technical issues or organizational impediments come up in the stand-up meetings.	4.92	1.48
DS4	Stand up meetings provide the quickest way to notify other members about problems.	5.07	1.68
DS5	When people report problems in the stand-up meetings, other members offer to help instantly.	5.31	1.34

**Retrospective Meetings** (Cronbach  $\alpha = 0.91$ ) (Source: So and Scholl (2009))

RET1	We actively participate in gathering lessons learned in the retrospectives.	5.56	1.53
RET2	The retrospectives help us become aware of what we did well in the past iteration/s.	5.73	1.38
RET3	The retrospectives help us become aware of what we should improve in the upcoming iteration/s.	5.73	1.40
RET4	In the retrospectives (or shortly afterwards), we systematically assign all important points or improvement to responsible individuals	4.75	1.66
RET5	We follow up intensively on the progress of each improvement point elaborated in a retrospective.	4.61	1.57

**Customer Access** (Cronbach  $\alpha = 0.89$ ) (Source: So and Scholl (2009))

CA1	The customer is reachable.	5.36	1.63
CA2	The developers can contact the customer directly or through a customer contact person without any bureaucratic hurdles	4.91	1.86
CA3	The developers have responses from the customer in a timely manner.	4.93	1.64
CA4	The feedback from the customer is clear and clarified about the requirements or open issues to the developers	4.90	1.56

All items were measured using a 7-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, 7 = strongly agree)

\* Items were measured using a 7-point Likert scale (1 = never, 2 = rarely, 3 = occasionally, 4 = sometimes, 5 = frequently, 6 = usually, 7 = every time)

Notes: The scores for each technical and social practice was computed by averaging their corresponding indicator items in order to form the higher level construct of technical agile practices.

## APPENDIX B

## CULTURAL &amp; CREATIVITY MEASURES

**Group (Quadrant I) Culture** (ICR = 0.829, AVE = 0.621) (Source: Iivari and Huisman (Iivari and Huisman 2007))

		<u>Mean</u>	<u>S.D.</u>
G1	The glue that holds the IT department I work in together is loyalty and tradition.	4.74	1.42
G4	The IT department I work in is a very personal place.	4.65	1.64
G3	The IT department I work in emphasizes human resources.	4.42	1.52

**Developmental (Quadrant II) Culture** (ICR = 0.840, AVE = 0.639) (Source: Iivari and Huisman (Iivari and Huisman 2007))

D1	The IT department I work in is a very dynamic and entrepreneurial place	4.75	1.60
D2	The glue that holds the IT department I work in together is commitment to innovation and development.	4.97	1.44
D3	The IT department I work emphasizes acquiring new resources and meeting new challenges.	4.72	1.36

**Rational (Quadrant III) Culture** (ICR = 0.785, AVE = 0.553) (Source: Iivari and Huisman (Iivari and Huisman 2007))

R1	The glue that holds the IT department I work in together is the emphasis on tasks and goal accomplishment.	4.97	1.33
R2	The IT department I work in is a very production-oriented place.	5.22	1.27
R3	The IT department I work in emphasizes competitive actions, outcomes and achievement.	4.43	1.64

**Hierarchical (Quadrant IV) Culture** (ICR = 0.863, AVE = 0.761) (Source: Iivari and Huisman (Iivari and Huisman 2007))

H1	The IT department I work in is a very formal and structured place.	3.50	1.71
H2	The glue that holds the IT department I work in together is formal rules and policies.	3.27	1.61

**Creativity** (ICR = 0.937, AVE = 0.748) (Source: Lee and Choi (Lee and Choi 2003))

C1	Our IT department has produced many novel and useful ideas (services/products).	5.45	1.16
C2	Our IT department fosters an environment that is conducive to our own ability to produce novel and useful ideas (services/products).	5.27	1.30
C3	Our IT department spends much time for producing novel and useful ideas (services/products).	4.76	1.41
C4	Our IT department considers producing novel and useful ideas (services/products) as important activities.	5.21	1.33
C5	Our IT department actively produces novel and useful ideas (services/products).	5.07	1.34

All items were measured using a 7-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, 7 = strongly agree)

## CHAPTER 4. TOWARDS THE DEVELOPMENT OF A BIG DATA CAPABILITY

### Abstract

The era of big data, which refers to unstructured, diverse, and fast moving data, has begun where organizations in all industries are increasingly collecting enormous volumes of data. While the research into the economic benefits of big data is in a nascent stage, organizations around the globe have been heavily investing in big data initiatives. However, we know from prior studies that investments alone do not generate competitive advantage; instead firms need to create capabilities that rival firms find hard to match (Bharadwaj 2000; Carr 2003). Drawing on the resource-based view of the firm and the recent work in big data, this study identifies various resources (e.g., technology, data, investments, and managerial and technical skills) that are needed by firms to build a big data capability. Further, this study categorizes these big data-specific resources into tangible, human, and intangible types. Specifically, this study examined the following research question: “What are the resources needed to create a firm-level big data capability?” Additionally, this study proposes and validates an instrument to measure a big data capability of the firm.



## Introduction

The information technology (IT) productivity paradox, which refers to the failure to establish a positive relationship between IT investments and firm productivity, has been the focus of several studies since the early 1990s. Eventually, the paradox was solved and more than two decades of research suggested several resources (e.g., managerial and technical skills, IT infrastructure, and firm's intellectual capital) that were required to realize the true value of investments in IT. While we have not yet witnessed the "big data productivity paradox," given the speed at which organizations in all industries and of all sizes are jumping on the bandwagon of big data (i.e., the new forms of data that need sophisticated technology to find meaningful patterns from them), it is likely that we, as information systems researchers, are waiting for it to happen. While in the 1980s, IT was touted as a competitive weapon, currently it is big data that is heralded as the next big thing for organizations to gain competitive edge. According to a recent global survey of 720 firms, 64% of organizations had already invested in or had plans to make investments in big data (Gartner 2013). This is surprising, given the research into the economic benefits of big data remains in an embryonic state. While the popular press, which is primarily written by technology consultants (or vendors), is rife with articles defining the characteristics<sup>1</sup> of big data, there is little knowledge about how organizations build big data capabilities.

We know from prior research that organizations build capabilities by combining and deploying their resources (Bharadwaj 2000; Grant 2010). This study considers data one such resource, which is necessary, but not sufficient to create a big data capability. In other words, big data on its own is unlikely to be a source of competitive advantage, since firms (of comparable sizes) will likely be collecting hordes of data from a variety of sources (Carr 2003). Similarly,

investments alone will not create superior big data capabilities (Ross et al. 2013). A firm needs a unique blend of its financial, physical, human, and organizational resources to create a capability, which will be difficult to match by competitors (Amit and Schoemaker 1993; Barney 1995; Grant 2010). Moreover, firms need to continuously reconfigure their resources according to changing market conditions (Teece 2014; Teece et al. 1997). However, to do so, it is imperative for firms to be aware of the various resources that are required to build a capability.

This study examines which resources are needed to build a big data capability, which we define as a firm's ability to assemble, integrate, and deploy its big data-specific resources. Drawing upon the resource-based view (RBV) of the firm, past IT capabilities literature, and recent work in big data, several resources are suggested. These resources are then categorized into tangible, human, and intangible types. Additionally, this study develops and validates an instrument to measure a firm's big data capability. It is hoped that academics interested in studying big data will use this instrument as a tool to further the research on big data, and practitioners can employ this instrument to assess current and future big data capabilities of their organizations and respond accordingly.

This paper is organized as follows. We begin with a brief review of relevant literature pertaining to RBV and big data. We then discuss different resources that create a big data capability. Next, we describe our research methods and data analysis for the big data capability instrument. The paper ends with a discussion of findings, followed by implications for practice and research.

## Literature

### The Resource-based view of the firm

The resource-based view has remained a principal paradigm to conduct research in the strategic management field, and the information systems (IS) field is no exception. According to RBV, a firm has a collection of tangible and intangible resources, but only the ones that are valuable, rare, inimitable, and non-substitutable (or simply VRIN) are capable of generating competitive advantage (Barney 1991). While Barney (1991) and other proponents of RBV do not explicitly differentiate between resources and capabilities, Amit and Schoemaker (1993) define resources as assets that are owned and controlled by a firm. By comparison, capabilities are defined as “a special type of resource” (Makadok 2001, p.385) that enables firms to aggregate and deploy their resources (in combination) to achieve a desired end (Amit and Schoemaker 1993). There are several types of resources that have been suggested in the extant literature. For example, according to Barney (1995, p. 50):

Financial resources include debt, equity, retained earnings, and so forth. Physical resources include the machines, manufacturing facilities, and buildings firms use in their operations. Human resources include all the experience, knowledge, judgment, risk taking propensity, and wisdom of individuals associated with a firm. Organizational resources include the history, relationships, trust, and organizational culture that are attributes of groups of individuals associated with a firm, along with a firm's formal reporting structure, explicit management control systems, and compensation policies

Grant (2010) further classifies these resources into tangible (e.g., financial and physical resources), people-based (e.g., employees' knowledge and skills), and intangible (e.g., organizational culture and organizational learning) resources.

Citing that RBV does not answer how some firms can quickly respond to changing market conditions, Teece et al. (1997) proposed the concept of dynamic capabilities, which refer to a firm's ability to “integrate, build, and reconfigure internal and external competencies to

address rapidly changing environments” (p. 516). According to the dynamic capabilities framework, the VRIN status of resources may become ordinary over time, and thus it is critical for firms to renew their resources in response to the external environment. The main point here is that ordinary capabilities (e.g., personnel, facilities, and equipment) can be sold or purchased in intermediate markets, while dynamic capabilities are built by a firm based on its heritage, culture, values, and learning abilities, which, according to DVF, are intangible assets.

### **Big data**

The term “big data” was initially coined to reflect the “bigness” or voluminous size of data generated as a result of using new forms of technology (e.g., social media, radio-frequency identification tags, smart phones, and sensors). This definition was then extended to include variety (i.e., structured or unstructured data formats) and velocity (i.e., the speed at which data are created) aspects of data. Over the years, others have further dimensionalized big data into veracity (i.e., messiness of data) and value (i.e., the previously unknown insights) (Davenport 2014). Indeed, these several Vs enhance our understanding of big data; however, the real potential of big data lies not in its properties, but in its affordance to a firm (Markus 2015). In industry, the term “big data” may also refer to the use of analytics (e.g., text analytics, social media analytics) to glean intelligence from unstructured data (Davenport 2014; LaValle et al. 2014). In sum, while there is no consensus on the definition and characteristics of big data, there is a complete agreement among scholars and practitioners on the transformational potential of big data (George et al. 2014; McAfee and Brynjolfsson 2012). For the purpose of this study, hereinafter the term “big data” will be used to describe massive, complex, and real time

streaming data that require sophisticated management, analytical, and processing techniques to extract insights (Beyer and Laney 2012).

### **Towards the development of a big data capability**

While the published research on big data is limited, there are some studies that have identified challenges associated with the success of big data projects. For instance, early studies suggested the size of data and lack of powerful computational technology as significant barriers to harness the potential of big data. A survey by New Vantage Group (2012) revealed that companies are more worried about the unstructured nature of data rather than the size of data. Some recent work indicates that big data initiatives are likely to fail unless organizations adopt a culture of data-driven decision making, where the senior-level executives make decisions based on data rather than on their instinct (Ross et al. 2013). Lack of managerial support is also cited as a critical factor impacting the success of big data initiatives (LaValle et al. 2014). Another challenge is to recruit fresh talent and train current employees in big data-specific skills since working with big data requires new kind of abilities, which are not commonly taught in universities (McAfee and Brynjolfsson 2012).

The research discussed so far lists several challenges that an organization may need to address to reap benefits from big data; however, it does not yield insights into how firms can create a big data capability. Relying on the resource-based perspective and additional work on RBV by several others (e.g., Amit and Schoemaker 1993; Grant 2010; Teece 2015), we propose seven resources, which are further categorized into tangible, human, and intangible resources (see Figure 1), that in combination will allow firms to create a big data capability. While tangible resources include data, technology, and other basic resources (i.e., time, and money), human

resources consist of managerial and technical skills pertaining to big data. Data-driven culture and the intensity of organizational learning are suggested as the two critical intangible resources needed to build a big data capability. We next discuss each of these resources in detail.

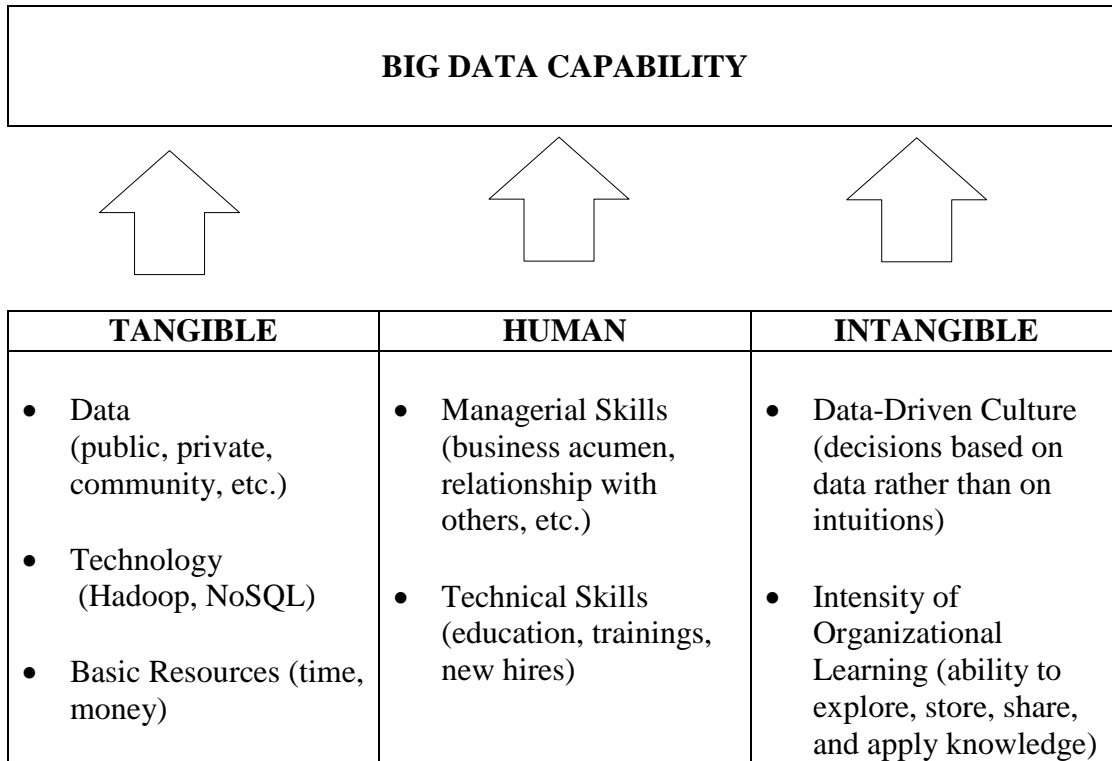


Figure 1. Classification of Big Data Resources

### Tangible resources

According to RBV, tangible resources are those that can be sold or bought in a market. Examples include financial resources (e.g., debt, equity) and physical assets (e.g., equipment and facilities) of the firm. Moreover, the firm's financial statement clearly describes its stock of tangible resources (Grant 2010; Teece 2014). Since tangible resources, to some extent, are readily available to all firms of comparable size (Barney 1991), these resources are unlikely to provide any competitive advantage on their own. Yet, tangible resources are required to create

capabilities. This study identifies data, technology, and basic resources (e.g., time, and money) as the three big data-specific tangible resources that are likely to be accessible to all firms.

### Data

The availability of sufficient data is critical for creating a big data capability. According to a recent McKinsey report, like labor, capital, and land, data are considered as an important factor of production by firms in all industries. While organizations in the past have primarily focused on enterprise-specific *structured* data (i.e., data that can be stored in relational databases) to make business decisions, today's organizations tend to capture every bit of information regardless of the size of data, structure of data, and speed at which data are created (Manyika et al. 2011). For instance, Walmart roughly collects 2.5 petabytes of data from its more than 1 million shopping transactions every hour (Knox 2013). Facebook adds 350 million new images every day to its existing database of more than 240 billion images (Miller 2013). It is not that organizations in the past did not have access to data; the recent advances in technology have led to the creation of new forms of data, which were unavailable as recently as ten years ago. Example of one such data includes data generated from radio-frequency identification (RFID) tags, which are heavily used all industries to track and identify objects in real-time. RFID tags create enormous amounts of data that are not only fast-moving, but are also highly complex.

George et al. (2014) identify five sources of (big) data: public data, private data, data exhaust, community data, and self-quantification data. Public data refer to government-owned data sets pertaining to healthcare, climate change, and consumer spending that are available to businesses (or individuals) for no cost. Private data are the firm-owned data that are actively collected by the firms. Examples include customer transactions, clickstreams, and data generated

from the use of RFIDs. Data-exhaust refers to the data that do not have a direct value attached to them. However, when combined with other sources of data, data-exhaust can yield new insights. Examples include random internet searches and location data generated from mobile phone usage. Data generated by users on online social communities, such as Facebook and Twitter, are considered community data. Finally, self-quantification data are personal data generated from wearable technologies such as fitness bands and smart watches. More broadly, a firm's data can be categorized into internal data and external data (Davenport 2014). While internal data refer to enterprise-specific data, which are created as a result of the firm's internal operations such as inventory updates, accounting transactions, sales, and human resource management, data collected from the sources external to an organization such as the web, e-commerce communities, mobile phones, and sensors can be termed as external data.

### Technology

New forms of data call for novel technologies that are capable of handling the challenges posed by gigantic, diverse, and fast moving data. Relational database management systems (RDBMS) have remained a popular choice for organizations to store structured data such as employees' records, customer orders, inventory management data, and financial transactions. Further, to gain insights from these disparate sources of organizational data, organizations have relied on extraction, transformation, and load (ETL) methods to design data warehouses (or data marts). Data warehouse is a collection of enterprise-specific data, which are extracted from various organizational functions and are then made to conform to a standard structure. Key performance indicators (KPI) are then extracted from data using online analytical processing, database queries, and other reporting services. This approach is useful and efficient as long as the



data that firms are dealing with are structured or in a format on which a structure can be easily imposed.

According to some estimates, as much as eighty percent of an organization's data exist in an unstructured format. This has forced organizations to move beyond traditional RDBMS methods of storing and analyzing data. Consequently, new technologies such as Hadoop, a Java based software framework, have emerged that allow distributed storage (via Hadoop Distributed File System or HDFS) and parallel processing (via MapReduce computational model) of massive unstructured datasets. HDFS is the lower level layer for distributed databases, commonly known as Not Only SQL (or NoSQL) databases that can efficiently store and retrieve non-relational unstructured data. Some examples of NoSQL databases include Cassandra, HBase, and MongoDB. Apple's recent acquisition of FoundationDB, a company that produces NoSQL databases, further emphasizes how critical these new forms of technology have become for organizations interested in gaining an edge over their competitors. Besides Hadoop and NoSQL database technologies, organizations further need several other technologies to store, process, analyze, and visualize big data.

In the past, proprietary technology has been considered a source of competitive advantage. A firm that can keep its proprietary technology secret is likely to have an edge over its competition (Carr 2003; Mata et al. 1995). However, prior studies suggest that in most cases it is difficult for firms to keep their proprietary technology hidden due to reasons such as labor force mobility and reverse-engineering (Mata et al. 1995). Moreover, the emergence of social media-based communities, such as LinkedIn groups and Meetups, enables individuals from different and sometimes competing organizations to engage in informal interactions as never

before. As a result, it is difficult for organizations to keep their (big data) technology completely secret from their rivals.

### Basic resources

Besides data and technology, firms need to make adequate investments in their big data-related initiatives. Moreover, given the newness of big data and its related technology and tasks, most organizations have yet to explore a standard procedure to implement these initiatives. Therefore, it is likely that a firm's big data initiatives may not start yielding desired results immediately. It is important that firms are persistent and devote enough time to their big data initiatives to achieve their analytical objectives. Based on this and consistent with prior IS research (Mata et al. 1995; Wixom and Watson 2001), this study suggests investments and time as two basic tangible resources required by a firm to create a big data capability.

### **Human resources**

A firm's human resources consists of its employees' experience, knowledge, business acumen, problem solving abilities, leadership qualities, relationships with others (Barney 1991; Ross et al. 1996). Prior IT capabilities research has suggested technical and managerial skills as the critical dimensions of human resources with respect to information technology (Bharadwaj 2000; Chae et al. 2014; Mata et al. 1995). Along the same lines, this study proposes big data-specific technical and managerial skills as two important aspects of a firm's human resources pertaining to big data.

### Technical skills

Technical “big data” skills refer to the know-how required to use new forms of technology to extract intelligence from big data. Some of these skills include competencies in machine learning, data extraction, data cleaning, statistical analysis, and understanding of programming paradigms like MapReduce. While some universities have started to offer courses in these skills, there is still a significant shortage of individuals with big data-specific technical skills (Chen et al. 2012). This is further vindicated by a recent McKinsey’s report that claims the United States alone will need 140,000 to 190,000 individuals with big data skills by 2018 (Manyika et al. 2011). Technical IT skills such as programming, database skills, and system analysis and design in general are not considered rare since these skills to a degree can be explicated (or codified) in procedures, documents, and manuals (Mata et al. 1995). We believe that same will apply to technical big data skills; however, given the newness of big data technology and the skills associated with it, organizations with big data-skilled employees are likely to have some advantage over their rivals. However, this advantage may not last long since, like technical IT skills, big data-specific technical skills may eventually get dispersed among individuals working in same (or different) organizations thereby making this resource ordinary across firms (Nonaka et al. 2000).

### Managerial skills

While firms can develop technical skills by hiring new talent and/or by training their current employees, managerial skills are highly firm-specific and are developed over time by individuals working in the same organization (Mata et al. 1995). These skills are developed as a result of strong interpersonal bond between organizational members working in same (or different) departments (Bharadwaj 2000). These skills are deep-rooted in an organization setting

and can be described as taken-for-granted norms through which managers perform their everyday work and make decisions (Bharadwaj 2000; Mata et al. 1995). Stated simply, managerial skills are tacit and thus are heterogeneously dispersed across firms (Mata et al. 1995).

Within the context of a firm's big data function, the intelligence gleaned from data will be of little use to an organization if its managers fail to foresee the potential of newly extracted insights. Thus, it is imperative for managers to have a sharp understanding of how and where to apply the insights extracted by their technical teams (Athey 2013). To do so, big data managers should have the ability to understand the current and predict the future needs of other business units, customers, and other partners (Mata et al. 1995). Moreover, mutual trust and a good working relationship between big data managers and other functional managers will likely lead to the development of superior human big data skills, which will be difficult to match by other firms.

### **Intangible resources**

Of the three principal types of organizational resources classified by Grant (2010) and other strategic management scholars, intangible resources are considered central to a firm's performance, especially in dynamic markets (Teece 2015). Yet, unlike tangible resources, intangible resources are not documented on firms' financial statements (Grant 2010). This is because intangibles resources do not have clear and visible boundaries, and their value is highly context-dependent (Barney 1995; Teece 2014). While most intangible resources are not easily tradable in a market, there are, however, some exceptions such as trademarks, copyrights, and other intellectual capital (e.g., patents), which can be sold or bought legally by organizations (Grant 2010). In general, most intangible resources meet the VRIN status of the resource-based

view thereby making them highly heterogeneous across firms. (Teece 2014). This study describes two such intangible resources that are likely to cause major heterogeneity across firms looking to reap benefits from big data. These resources are data-driven decision making culture and intensity of organizational learning.

### Data-driven culture

Organizational culture is a highly complex notion to understand and describe. Over the years, management scholars have suggested several definitions of organizational culture, yet there is no consensus on a single definition (House et al. 2002). While some suggest that organizational culture encompasses nearly all areas of an organization, others call it a glue that keeps an organization together (Dowling 1993; Iivari and Huisman 2007). Prior studies in management strategy have identified organizational culture as a source of sustained firm performance (Barney 1986; Barney 1995; Teece 2015). On the same lines, recent work in big data suggests that organizational culture is critical for the success of the firm's big data initiatives. For instance, Lavallo et al. (2014) indicate that the reasons why big data projects are often unproductive relate to organizational culture rather than to the characteristics of data and lack of technology. Ross et al. (2013) opine that culture has the ability to inhibit (or enhance) an organization's ability to benefit from big data.

This emerging stream of research on big data further asserts that while organizations in all industries are collecting hordes of data, only a small percentage of organizations have actually benefitted from their big data investments (Ross et al. 2013). This is because most organizations rely on the past experience and/or intuition of their top-executives to make important decisions, which is commonly referred to as the highest paid person's opinion (HIPPO) (McAfee and

Brynjolfsson 2012). To realize the full potential of data owned by firms, it is critical that firms develop a data-driven culture, which this study, following Ross et al. (2013) and McAfee and Brynjolfsson (2012), defines as the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data. A firm in which decisions are influenced by the title (or designation) of some individuals is unlikely to gain any return on its big data investments. Consequently, the efforts to collect massive amount of data, acquire technology, and build technical and managerial skills will be in vain. Moreover, given employees at all levels in an organization are required to make some decisions, it is pertinent to diffuse the culture of data-driven decision making to all levels such that organizational members, regardless of their titles, have the ability to make good decisions that are grounded on some tangible evidence as suggested from data (Ross et al. 2013).

#### Intensity of organizational learning

The resource-based view is often criticized for failing to address why some firms perform better than their rivals, especially in rapidly changing market conditions (Eisenhardt and Martin 2000). According to Teece et al. (1997), firms that have the ability to reconfigure their resources according to the changes in their external environment will likely have a sustained competitive advantage. Grant (1996) asserts that this ability of a firm will likely be impacted by its intensity of organizational learning, which is a process through which firms' explore, store, share, and apply knowledge (Bhatt and Grover 2005; Cohen and Levinthal 1990). This makes sense because organizational knowledge never wears out (Nonaka and Teece 2001). Grant (1996) further proposed the knowledge-based view of a firm that views firms as institutions in which

specialized knowledge of individuals is integrated to form organizational-level knowledge that in turn leads to sustained business performance.

Though knowledge does not wear out, it may become outdated due to the emergence of new technologies (or new inventions) (Nonaka and Teece 2001). Therefore, firms need to have concerted efforts to exploit their existing knowledge and explore new knowledge to cope with the uncertain market conditions (Bhatt and Grover 2005; Teece 2015). Based on this, it is safe to suggest that firms with high intensity of organizational learning are likely to have stocks of organizational knowledge that can be used towards creating a big data capability. These stocks of (new and old) knowledge can be combined with the insights extracted from big data to make informed decisions. We know that any analysis of data does not tell the whole story; it is always the theory that explains. In the same manner, firms with high intensity of organizational learning will likely have an advantage of applying their stocks of knowledge to further validate the initial insights gleaned from big data.

### **Big data capability**

Drawing on RBV, we have proposed that firms need a combination of certain tangible, human, and intangible resources to build a big data capability. Prior studies, citing that tangible resources can be acquired from a market, have emphasized the importance of human and intangible resources in creating organizational capabilities. While we agree that big data-specific tangible resources on their own cannot create a big data capability, we believe this is true for human and intangible big data resources as well. To create a big data capability, a firm needs not just one or two of these resources, but it is the unique combination of all three that generates a firm-specific big data capability. For instance, a firm that has a corpus of data and powerful

computational technology, but lacks managerial and technical big data skills, is unlikely to benefit from its data and big data technology. Similarly, the mere presence of tangible resources (e.g. data and technology) and big data-specific human skills will not be rewarding if an organization lacks learning intensity and adopts a culture where decisions are made based on people's opinions.

Having defined the notion of big data capability and the resources that in combination build this capability, we next develop an instrument to measure a firm's big data capability.

## **Instrument Development**

### **Conceptualization of constructs**

As discussed previously, this study defines big data capability as a firm's ability to assemble, integrate, and deploy its big data-based resources. Specifically, the big data capability construct is conceptualized as a multi-dimensional third-order aggregate (or formative construct) of big data-specific tangible, human, and intangible resources constructs, which in turn are conceptualized as second-order formative constructs comprising of first-order constructs (see Table 1). Measures of all the first-order constructs, except data-driven culture, were adapted from the existing scales proposed in the literature; however, given the new context of the current study, the items were modified accordingly (see Table 2). For the data-driven culture construct, the recent work in big data was examined and five items were generated, as shown in Table 2. All items were further examined by the authors and a person in industry with big data knowledge.

We know that constructs are not inherently formative or reflective; it depends on how they are conceptualized within research. Since this study employs a mix of reflective and



formative constructs, we followed the guidelines of Jarvis et al. (2003) to evaluate if the constructs proposed in this study as formative were in fact formative. To do so, we assessed the direction of causality from the constructs to their measures, interchangeability of the items, and covariation among the indicators of the same construct (Petter et al. 2007). For all formative constructs proposed in this study, the indicators collectively define their constructs such that changes in indicators are likely to cause a change in their corresponding constructs. Second, the items of the formative constructs in our study are not interchangeable. For example, the big data capability construct is suggested as an aggregate of intangible, tangible, and human resources constructs. These three sub-dimensions capture a different aspect of the big data capability construct and clearly are not interchangeable. We further do not necessarily expect intangible, tangible, and human resources dimensions to covary with each other. Like the big data capability construct, all other formatively-proposed constructs satisfied the criteria suggested by Jarvis et al. (2003).

Table 1. Latent Constructs and Sub Dimensions

Third-order	Type	Second-order (sub-dimensions)	Type	First-order (sub-dimensions)	Type
Big Data Capability	Formative	Tangible Resources	Formative	Data	Formative
				Technology	Formative
				Basic Resources	Formative
		Human Resources	Formative	Managerial Skills	Reflective
				Technical Skills	Reflective
				Firm-specific skills	Reflective
		Intangible Resources	Formative	Data-driven culture	Reflective
				Intensity of Organizational Learning	Reflective
				Relationship Asset	Reflective

Table 2. First-Order Constructs and their Items

Construct	Item	Source
Data	We have access to very large, unstructured, or fast-moving data for analysis	(Davenport 2014)
	We integrate data from multiple internal sources into a data warehouse or mart for easy access	
	We integrate external data with internal to facilitate high-value analysis of our business environment	
Technology	We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing	(Davenport 2014)
	We have explored or adopted different data visualization tools	
	We have explored or adopted cloud-based services for processing data and doing analytics	
	We have explored or adopted open-source software for big data and analytics	
	We have explored or adopted new forms of databases, such as Not Only SQL (NoSQL), for storing data.	
Basic Resources	Our big data and analytics projects are adequately funded	(Wixom and Watson 2001)
	Our big data and analytics projects are given enough time to achieve their analytical objectives	
Technical Skills	We provide big data and analytics training to our own employees	(Carmeli and Tishler 2004; Mata et al. 1995)
	We hire new employees that already have the big data and analytics skills	
	Our big data and analytics staff has the right skills to accomplish their jobs successfully	
	Our big data and analytics staff has suitable education to fulfill their jobs	
	Our big data and analytics staff holds suitable work experience to accomplish their jobs successfully	
	Our big data and analytics staff is well-trained	
Managerial Skills	Our big data managers understand and appreciate the business needs of other functional managers, suppliers, and customers.	(Davenport 2014; Mata et al. 1995)
	Our big data managers are able to work with functional managers, suppliers, and customers to determine opportunities that big data and analytics might bring to our business	
	Our big data managers are able to coordinate big data and analytics activities in ways that support other functional managers, suppliers, and customers	
	Our big data managers are able to anticipate the future business needs of functional managers, suppliers, and customers	
	Our big data managers have a good sense of where to apply big data and analytics	
	Our big data managers are able to understand and evaluate the output from big data and analytics	

Data-Driven Culture	We consider data a tangible asset	(Laney 2001; McAfee and Brynjolfsson 2012; Ross et al. 2013)
	We base our decisions on data rather than on instinct	
	We are willing to override our own intuition when data contradict our viewpoints	
	We continuously assess and improve the business rules in response to insights extracted from data	
	We continuously coach our employees to make decisions based on data	
Intensity of Organizational Learning	We are able to search for new and relevant knowledge	(Bhatt and Grover 2005)
	We are able to acquire new and relevant knowledge	
	We are able to assimilate relevant knowledge	
	We are able to apply relevant knowledge	
	We have concerted efforts for the exploitation of existing competencies and exploration of new knowledge.	

### Hierarchical model specification

The model was then formally specified, representing the relationships between the indicators, sub-dimensions, and higher-order constructs (see Figure 2). Following Wetzels et al. (2009), we first constructed the first-order latent variables and connected them to their corresponding indicators. Data, technology, and basic resources constructs were modelled as mode B “formative,” while the remaining first-order constructs were connected to their indicator items as mode A “reflective.” The second-order latent variables were then constructed by repeating the indicators of their underlying first-order latent variables using mode B “formative” method. Thus, the tangible resources construct was made up of the indicators of basic resources, data, and technology, while the human resources construct was connected to the indicators of managerial skills and technical skills constructs. The intangible construct was linked to the indicators of data-driven culture and the intensity of organizational learning constructs. Finally, the third-order latent variable big data capability was constructed by repeating the indicators of its second-order constructs.

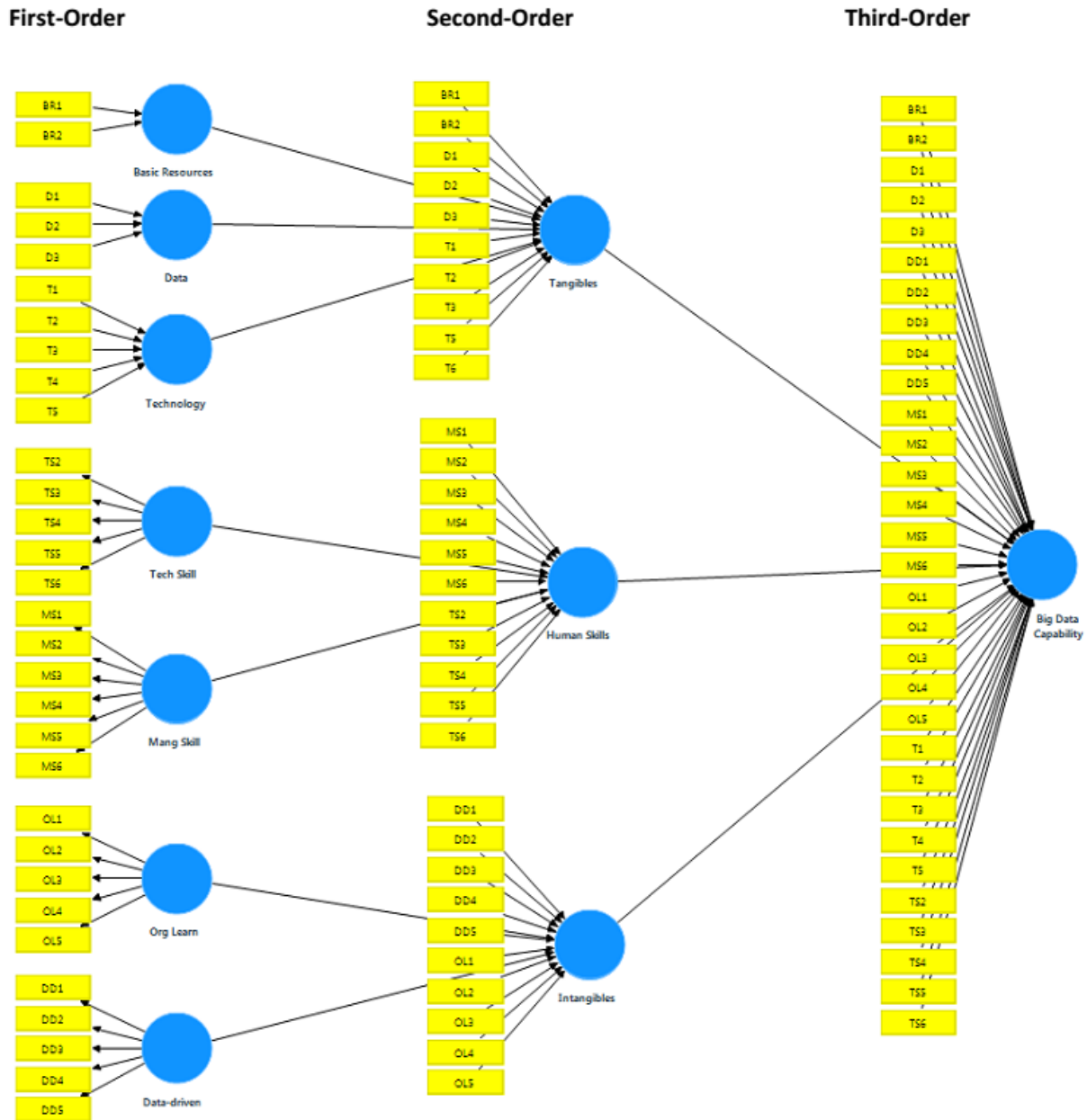


Figure 2. Hierarchical Model Specification Using Repeated Indicators Approach

### Data collection

Having formally specified the measurement model, a survey was then created in Qualtrics. The survey was sent to 1,000 senior level managers involved in big data initiatives.

The respondents were selected from the *Big Data and Analytics* group on LinkedIn. In total 232

responses were received. Respondents represented a variety of industries (e.g., computers, financial services, internet, communications and utilities), and their job titles included chief information officer, chief technology officer, vice president of technology, director of information technology, managers of analytics, chief data scientist, and senior data scientist. Given we had data collected on 34 indicators, we first conducted an exploratory factor analysis (EFA) using principal component analysis (PCA) and varimax rotation. Seven factors emerged (eigenvalues  $>1$ ). All items loaded on their related factor as expected except for TS1, which had significant loadings ( $> 0.5$ ) across multiple factors. Consequently, TS1 was dropped from further analysis (Hair et al. 2006). The hierarchical model was then estimated using the PLS path weighting scheme, which is the recommended method for estimating hierarchical latent variables, especially when the measurement model contains formative constructs (Becker et al. 2012; Rigdon et al. 2014).

### **Model assessment**

The assessment criteria for formative and reflective constructs are different. We first assessed the validity of the indicators at the construct level. For reflective constructs, all of the items had outer loadings above 0.7 and the average variance extracted (AVE) of all measures exceeded 0.50 (Hair Jr et al. 2013). While all of the indicators' weights of data and basic resources were statistically significant, only three of the five indicators' weights of the technology construct were found significant. Cenfetelli and Bassellier (2009) suggest that a formative construct with many indicators is likely to have few indicators with non-significant weights. They further suggest that the non-significant indicator of a formative construct can be kept in a model as long as the researchers can justify the contribution of it. Given that the

technology construct is proposed as an aggregate of five items where each item captures a different big data-related technology, we believed it was appropriate to keep the non-significant indicators in the model as each item made an important and distinct contribution to the overall technology construct.

Following MacKenzie et al. (2011), we then evaluated the validity of the items of the formative constructs using Edwards' (2001) adequacy coefficient ( $R^2_a$ ) by summing the squared correlations between the formative construct and its indicators and then dividing the sum by the number of indicators. All  $R^2_a$  values were above 0.50 (see Table 3), suggesting that the majority of the variance in the indicators is shared with the formative construct, and thus the indicators of the formative construct are valid (MacKenzie et al. 2011). Like the first-order formative constructs, we first evaluated the weights of the formative indicators on their respective higher-order constructs (three second-order and one third-order constructs). All weights were highly significant. The Edwards' adequacy coefficients ( $R^2_a$ ) for the higher-order constructs were then calculated. All  $R^2_a$  values were greater than the recommended values of 0.50 (MacKenzie et al. 2011).

Table 3. Higher-order Construct Validation

Construct	Measures	Weight	Significance	VIF	$R^2_a$ *
Data	D1	0.53	p < 0.001	1.376	0.78
	D2	0.26	p < 0.05	1.466	
	D3	0.48	p < 0.001	1.281	
Technology	T1	0.18	p < 0.05	1.795	0.70
	T2	0.70	p < 0.001	1.529	
	T3	0.02	ns	1.541	
	T4	0.12	ns	1.61	
	T5	0.20	p < 0.05	1.887	
Basic Resources	BR1	0.54	p < 0.001	2.249	0.88
	BR2	0.28	p < 0.01	1.977	

Tangibles	Data	0.34	p < 0.001	1.72	0.84
	Technology	0.37	p < 0.001	1.82	
	Basic Resources	0.47	p < 0.001	1.65	
Human	Managerial Skills	0.40	p < 0.001	1.79	0.91
	Technical Skills	0.69	p < 0.001	1.79	
Intangibles	Data-Driven Culture	0.49	p < 0.001	1.50	0.88
	Organization Learning	0.63	p < 0.001	1.50	
BDA	Tangibles	0.42	p < 0.001	2.34	0.91
	Human	0.31	p < 0.001	2.84	
	Intangibles	0.37	p < 0.001	2.88	

\* Edwards (2001) adequacy coefficient

We then examined the extent to which the indicators of the formative constructs were multicollinear with each other. While multicollinearity is desired among the indicators of a reflective construct, it is problematic for formative constructs. Variance inflation factor (VIF) values below 10 in general demonstrate low multicollinearity (MacKenzie et al. 2011); however, Petter et al. (2007) suggest a more restrictive cutoff of 3.3 for formative constructs. VIF values for all the measures of the first-order, second-order, and third-order formative constructs in this study were less than 3.3 (see Table 3), indicating that multicollinearity was not a major concern (Cenfetelli and Bassellier 2009; Petter et al. 2007).

### Reliability and discriminant validity

The concept of internal consistency reliability (ICR) does not apply to formative constructs; however, for reflective constructs, the reliability was assessed using ICR and Cronbach's  $\alpha$ , both of which were above 0.8 for all constructs (see Table 4). Discriminant

validity of the reflective constructs was established using Fornell and Larcker's (1981) criteria. The square root of the AVEs of each latent variable was greater than its correlation with any other constructs. Examination of cross-loadings further yielded support for discriminate validity (see Table 5). Recently, Hensler et al. (2014) have criticized the Fornell and Larcker's (1981) criterion of assessing the discriminant validity and have suggested a new criterion called the heterotrait-monotrait ratio (HTMT). The HTMT ratio is based on the average of the correlations of indicators across constructs measuring different phenomena relative to the average of the correlations of indicators within the same construct. According to Hensler and colleagues (2014), the HTMT ratio below 0.85 demonstrates sufficient discriminant validity. We ran this test on the first order reflective constructs, and the HTMT values for all reflective constructs were found below 0.85. Please note that HTMT method can only be used to assess the discriminant validity of reflective constructs (Hensler et al. 2014).

Table 4. Inter-correlations of the Latent Variables for First-Order Constructs\*

	Construct	ICR	Alpha	AVE	1	2	3	4	5	6	7
1	Data	NA	NA	NA	NA						
2	Basic Resources	NA	NA	NA	0.54	NA					
3	Technology	NA	NA	NA	0.60	0.58	NA				
4	Managerial Skills	0.92	0.87	0.79	0.45	0.57	0.47	<u>0.89</u>			
5	Technical Skills	0.93	0.89	0.76	0.53	0.61	0.55	0.67	<u>0.87</u>		
6	Data-Driven Culture	0.90	0.86	0.70	0.54	0.48	0.52	0.64	0.71	<u>0.84</u>	
7	Organization Learning	0.94	0.92	0.75	0.53	0.53	0.57	0.56	0.58	0.58	0.87

\* Square root of the AVEs on the diagonal

To the best of our knowledge, there are no established tests in prior literature to assess the discriminant validity of formative constructs (Hensler et al. 2014). There are two recommendations, however. MacKenzie et al. (2011) suggest that the formative construct should



less than perfectly correlate (i.e., less than 0.71) with other constructs. Klein and Rai (2009) suggest that, like reflective items, indicators of the formative constructs should load highly on their corresponding constructs in comparison to other constructs. All of the first-order formative (and reflective) constructs in our study satisfy both of these conditions (see Table 4 and Table 5).

Table 5. Cross-Loadings

Items	Data	Technology	Basic Resources	Managerial Skills	Technical Skills	Data-Driven	Org Learning
D1	<b>0.82</b>	0.51	0.46	0.36	0.42	0.44	0.46
D2	<b>0.73</b>	0.44	0.37	0.42	0.42	0.42	0.37
D3	<b>0.79</b>	0.45	0.43	0.46	0.42	0.42	0.40
T1	0.45	<b>0.66</b>	0.37	0.30	0.38	0.28	0.36
T2	0.55	<b>0.93</b>	0.53	0.50	0.51	0.50	0.53
T3	0.31	<b>0.59</b>	0.38	0.35	0.36	0.23	0.30
T4	0.34	<b>0.65</b>	0.42	0.32	0.39	0.29	0.40
T5	0.42	<b>0.68</b>	0.41	0.32	0.40	0.29	0.39
BR1	0.52	0.55	<b>0.93</b>	0.54	0.57	0.44	0.48
BR2	0.44	0.47	<b>0.82</b>	0.49	0.49	0.40	0.46
MS1	0.47	0.43	0.48	<b>0.85</b>	0.53	0.61	0.53
MS2	0.50	0.49	0.48	<b>0.87</b>	0.62	0.61	0.58
MS3	0.46	0.44	0.52	<b>0.90</b>	0.62	0.62	0.56
MS4	0.42	0.39	0.50	<b>0.85</b>	0.60	0.50	0.50
MS5	0.41	0.46	0.51	<b>0.84</b>	0.60	0.59	0.47
MS6	0.39	0.41	0.51	<b>0.83</b>	0.60	0.61	0.52
TS2	0.46	0.44	0.50	0.48	<b>0.73</b>	0.40	0.53
TS3	0.48	0.53	0.56	0.64	<b>0.91</b>	0.55	0.64
TS4	0.46	0.49	0.53	0.66	<b>0.91</b>	0.55	0.66
TS5	0.46	0.45	0.53	0.60	<b>0.89</b>	0.52	0.63
TS6	0.46	0.52	0.62	0.64	<b>0.91</b>	0.53	0.63
DD1	0.35	0.25	0.28	0.40	0.39	<b>0.69</b>	0.47
DD2	0.48	0.45	0.37	0.52	0.45	<b>0.84</b>	0.42
DD3	0.39	0.45	0.42	0.51	0.48	<b>0.83</b>	0.49
DD4	0.52	0.45	0.44	0.69	0.55	<b>0.84</b>	0.56
DD5	0.41	0.39	0.38	0.60	0.46	<b>0.79</b>	0.46
OL1	0.48	0.43	0.42	0.52	0.61	0.50	<b>0.86</b>
OL2	0.41	0.45	0.42	0.51	0.60	0.50	<b>0.90</b>
OL3	0.45	0.49	0.43	0.55	0.61	0.52	<b>0.90</b>
OL4	0.51	0.52	0.49	0.56	0.61	0.57	<b>0.88</b>
OL5	0.45	0.58	0.56	0.54	0.64	0.52	<b>0.81</b>

## Discussion

This study identified various resources that build a big data capability. To do so, we relied on the resource-based view, past IT capabilities literature, and published work in big data. Following Grant (2010), this study further categorized these resources into tangible, human, and intangible resources. Specifically, (big) data and technology are suggested as the two necessary tangible resources, and managerial and technical big data-specific skills are identified as the important human skills. In addition to tangible and human resources, firms need to construct intangible resources such as data-driven culture and the intensity of organizational learning. This study then developed an instrument to evaluate a firm's big data capability. Several tests were performed to assess the psychometric properties of the instrument. Given that the instrument consists of higher-order formative constructs, extra caution was taken in terms of model specification and model assessment. Consequently, we followed several guidelines available in the extant literature to avoid model misspecification and correctly assess the validity of the indicators and the constructs (e.g., Becker et al. 2012; Cenfetelli and Bassellier 2009; MacKenzie et al. 2011; Petter et al. 2007). For instance, we modelled higher-order constructs (i.e., tangible, human, intangible, and big data capability) using mode B "formative" method. We used the more restrictive VIF cutoff value of 3.3 to examine multicollinearity rather than cutoff values of 5 and 10, which are also suggested in literature. For reflective constructs, in addition to Fornell and Larcker's (1981) criteria and the examination of cross-loadings, we used the HTMT ratio to establish the discriminant validity of the first-order latent variables. In sum, the hierarchical model demonstrated good psychometric properties.

## Implications

The present study yields some interesting insights for practice. While the extant research yields some limited insights into the challenges pertaining to big data, most of this research remains fragmented. This study attempts to unify this stream of research by focusing on how firms can address these challenges by acquiring (or building) appropriate resources. While data, technology, and technical skills are some obvious resources that have garnered attention from organizations, this study suggests that managerial big data skills, data-driven culture, and the intensity of organizational learning are further needed if a firm desires to outdo its rivals. Further, this study presents an instrument to measure a big data capability, which can be employed by firms to assess their current and future big data capabilities.

The findings of this study also provide valuable contributions to the growing body of research on big data. The majority of the extant literature on big data has been contributed by practitioners (or vendors), who are more interested in the properties (or dimensions) of big data and big data-related technology. Consequently, this stream of research lacks theoretical insights. This research, by utilizing RBV as a theoretical lens, identifies various resources that form a firm's big data capability. This way, this research is an early attempt to examine the big data phenomenon using established management theories. Additionally, this study proposes and operationalizes the construct of big data capability, which can be further utilized by researchers interested in studying big data-specific topics in the future. This study also makes a significant contribution to an ongoing discussion on formative constructs (Aguirre-Urreta and Marakas 2014; Rigdon et al. 2014). Furthermore, this study employs formative constructs at different levels (first-order, second-order, and third-order) and provides a step-by-step approach to avoid misspecification of formative constructs, a topic that has gained considerable attention recently

in the information systems field (Becker et al. 2012; Gudergan et al. 2008; Hair et al. 2011; Rigdon et al. 2014; Ringle et al. 2012).

### **Limitations and future research**

Like any other study, this study is not without limitations. First, it is possible that this study might have missed some resources that may equally contribute to the development of a firm's big data capability. Consequently, the research presented in this study can be further extended to include more big data-specific tangible, human, or intangible resources. Second, the instrument proposed in this study was validated using only one set of data that were collected from an online LinkedIn community. Further, the respondents in this study were employed at US-based organizations. So, another avenue for future research is to further validate this instrument by collecting data from different (or non-LinkedIn) sources and respondents from different countries. This would further establish the reliability and validity of its measures. Third, this study utilizes partial least squares-structural equation modeling (PLS-SEM), which has attracted a lot of criticism from the proponents of covariance-based (CB) SEM. We suggest that future work in this area can further evaluate the hierarchical latent model presented in this study using CB-SEM.

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## CHAPTER 5. CONCLUSION

### Conclusions from the Three Studies

The three studies in this dissertation were aimed at extending our understanding of culture in the information systems field. As discussed previously, there are several challenges pertaining to the definition and conceptualization of the notion of culture, however, despite these challenges, the concept of culture is termed critical to understand national, organizational, group, and individual-level behaviors. This dissertation consists of three studies (study 1, study 2, and study 3) where each study examined the impact of a different level of culture (e.g., national, organizational, and data-driven) in three different information systems-related research contexts. While study 1 focused on national culture and examined its role in computer-mediated deceptive communication, study 2 employed the competing values framework of organizational culture and examined how different forms of organizational culture (e.g., group, developmental, rational, and hierarchical) affect the implementation of agile practices in organizations. Study 3 looked at the data-driven decision making aspect of organizational culture, which along with other resources such as managerial and technical skills, and organizational learning, would create a big data capability. Specifically:

*Study 1* investigated the effects of four communication media and national culture on individuals' ability to detect deception. Drawing upon leakage theory and media synchronicity theory, this study hypothesized that deception detection rates would be highest for the judgments made from audiovisual media, followed by video only, audio only, and text only media. The results did not support this proposed ranking. Participants were better able to detect deception from audio only media (63.5%), followed by audiovisual (57.9%), text only (55.5%), and finally

video only media (53.5%). Further, only audio media was found statistically different from text and video only media. This study also hypothesized that individuals would be better able to detect deception in the outside culture than within their own culture. The results yielded support for this hypothesis. American participants detected deception more accurately from the stimulus sets featuring Indians than from the ones featuring Americans. Additionally, the deception detection rates were more accurate when Indian participants spoke in their second (English) language than when they spoke in their native (Hindi) language. This study also observed significant interaction effects between media and culture.

This study has significant implications for practice and research. For practice, the findings suggest that, by examining irregularities in the speaking styles of non-native speakers, native speakers are capable of detecting deception in the outside culture. Further, contrary to a common assumption that links media capability to transmit more cues to higher deception detection rates, this study found that American judges made more accurate judgments from audio only media, compared to text and video only media. Too few cues in video only and text only media seem to impede judges' ability to correctly identify deception. For research, by examining deception and its detection across different media, this study makes an important contribution to deception literature, which has primarily focused on real-time face-to-face conversations. Additionally, contrary to prior research that treats culture and language as two separate entities, this study considered culture and language tightly intertwined with each other, and examined their collective impact on deception detection. Furthermore, by examining the deception detection capabilities of American participants within their own culture and in the outside Indian culture, this study extends our understanding of deception and its detection across different cultures.

*Study 2* examined the impact of four organizational cultural forms on two agile systems development practices, and how these practices influenced creativity, when applied to IT departments. While hierarchical culture negatively influenced both social and technical agile practices, developmental culture was found to have a positive impact on the two ASD practices. This study hypothesized that rational culture would likely have a negative influence on the use of social agile practices; however, this hypothesis was not supported. On the other hand, rational culture had a positive relationship with the use of technical agile practices. By comparison, while group culture was found to have a positive influence on social practices usage, the proposed negative relationship between group culture and technical agile practices was not supported. Further, as hypothesized, both technical and social agile practices increased organizational creativity, when applied to IT departments.

This study yields some interesting insights for practice. Contrary to existing research, this study found that there is no ideal agile culture and, except for hierarchical culture, agile practices can be successfully followed in a range of organizational cultures. The only cultural form which IT managers interested in implementing agile methodologies should be wary of is hierarchical culture. Additionally, there was some support to suggest that cultural forms impact social and technical agile dimensions differently. While group, developmental, and rational forms of culture were found to encourage social agile practices, only developmental and rational culture had a significant positive relationship with technical agile practices. This suggests that IT managers of group culture-oriented organizations should invest more in social practices rather than in technical practices.

Further, compared to prior research that has largely focused on case or ethnographic studies, this study adopted a survey method, thereby making the findings more generalizable

across organizations. The unit of the analysis in this study was the IT department instead of a team or a project. This study suggested that since organizations were more likely to introduce agile practices across their IT departments, it was reasonable to assess the impact of using these practices at the IT department-level. Additionally, while the importance of creativity in systems development is well-recognized in practice, the construct of creativity has received scant attention in the information systems development literature. By focusing on creativity as the outcome of using agile practices, this study extends our understanding of the scarcely studied concept of creativity in the management information systems literature.

*Study 3* suggested different resources that create a big data capability. Using the resource-based view of the firm and prior work in IT resources/capabilities literature, this study proposed seven resources that in combination would generate a firm-level big data capability, which in turn might lead to superior firm performance. These seven big data-specific resources are data, technology, basic resources (e.g., adequate investments, sufficient staff, and time), managerial “big data” skills, technical “big data” skills, data-driven culture, and intensity of organizational learning. While data, technology, and basic resources were termed as tangible resources, managerial and technical skills were considered human resources. Data-driven culture and intensity of organizational learning were proposed as the two intangible resources. This study argued that only the firms that have the ability to develop a unique combination of these seven resources would likely harness the true potential of their big data. Consistent with recent work in big data, this study suggests that organizations that primarily rely on the past experience and intuition of their top-executives to make important decisions are less likely to benefit from their big data investments. Besides investments, big data-specific human skills, and the intensity of organizational learning firms must develop and promote a data-driven decision making culture

where employees at all levels, irrespective of their job titles, are capable of making good decisions.

Based on survey data collected from 232 experienced big data, this study developed the big data capability instrument. The instrument demonstrated good psychometric properties thereby providing support for the importance of seven resources suggested in this study in creating a firm-specific big data capability. This study also has implications for practice and research. Practitioners can employ the big data capability instrument to evaluate current and future big data capabilities of their organizations. Additionally, this study proposes and operationalizes the construct of big data capability, which can be further utilized by scholars to further the research on big data in the future. Furthermore, the existing literature on big data has primarily been contributed by practitioners. Consequently, this stream of research lacks theoretical insights. By using the resource-based perspective of the firm, this study attempted to understand the big data phenomenon through a theoretical lens of established management theories.