

**Mechanisms driving technology use in the  
context of digital inequality:  
A series of essays on the role of social  
influence, socio-cognitive processes, and  
socio-economic determinants**

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## Table of contents

**Preface .....1**

**Social influence in technology adoption research: A literature review and future research agenda .....14**

Katharina Buhtz

*Submitted to the European Journal of Information Systems (EJIS)*

**Mechanisms of engagement with, and disengagement from, Internet applications: A qualitative study of online job search.....89**

Annika Reinartz, Katharina Buhtz

*Submitted to the Journal of the Association for Information Systems (JAIS)*

**Second-order digital inequality: A clickstream analysis of e-commerce use .....132**

Katharina Buhtz, Annika Reinartz, Andreas König, Lorenz Graf-Vlachy, Jan Mammen

*Submitted to the International Journal of Electronic Commerce (IJEC)*

**Bridging digital inequality: What can public policy makers do to ensure equal benefit from online opportunities?.....182**

Katharina Buhtz, Annika Reinartz

*Submitted to the Communications of the ACM (CACM)*

**Concluding remarks .....198**

[Supplement A] Second-order digital inequality: The case of e-commerce (as published in The Proceedings of the ICIS 2014) .....205

[Supplement B] Second-order digital inequality: The case of e-commerce (presentation held at ICIS 2014).....228



## Preface

Information systems (IS) scholars have long sought to understand *why* and *how* individuals adopt and use new information technologies. With the advent of computer and information technologies in the business and private space in the 1980s, researchers began to explore the reasons why individuals adopt and use these new technologies or refrain from doing so. Drawing on sociology, psychology, and information systems research, two seminal theoretical models were developed that serve as the founding pillars of technology adoption research to this day. The first is Davis' (1989) Technology Acceptance Model (TAM), which identifies perceived usefulness and perceived ease of use as the two major antecedents of an individual's intention to use a new technology and subsequent actual use. The second is Ajzen's (1991) Theory of Planned Behavior (TPB), which posits that attitude, subjective norm, and perceived behavioral control are significant predictors of intention to use and actual use of a technology. Over time, these founding theories have been enriched by additional antecedents as they were adapted to work- and non-work contexts (Peng, Dey, & Lahiri, 2014; Tsai & Bagozzi, 2014), mandatory and voluntary contexts (Chatterjee, Sarker, & Valacich, 2015; Magni, Angst, & Agarwal, 2013), and tested for moderating effects (see Venkatesh, Morris, Davis, & Davis (2003) for an overview). Today, models like the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh, Thong, & Xu, 2012) are able to account for over 70% of variance in behavioral intention to use. As such, they serve as an insightful theoretical lens through which to study technology adoption and use.

With the increasing spread of computer and information technology, scholars have voiced concerns that not all individuals are taking part equally in the digital revolution (Hargittai, 2003). They termed this societal phenomenon "digital inequality", thereby specifically referring to the unequal opportunities and abilities of individuals to benefit from (Internet-based) information and communication technologies (ICT) (DiMaggio, Hargittai, Coral, & Steven, 2004). More specifically, scholars distinguish between two main levels. 'First-order' digital inequality relates to differences in ICT access and adoption, and is concerned with *whether* individuals use ICT (DiMaggio & Hargittai, 2001). This has garnered the majority of research attention to date and continues to be an important issue particularly in developing countries (Agarwal, Animesh, & Prasad, 2009; Dewan, Ganley, & Kraemer, 2010). 'Second-order' digital inequality, in contrast, is concerned with *how* individuals use, or appropriate, ICT. This has evolved into the dominant issue in more developed markets with high ICT

penetration rates, yet has so far received less scholarly attention (Gui & Argentin, 2011; Riggins & Dewan, 2005).

Today, despite arduous efforts to counter the issue on the one hand and contrary to claims that the issue will resolve itself on its own on the other, digital inequality remains a relevant societal concern (van Deursen & van Dijk, 2014). In fact, the high Internet penetration rates particularly in developed countries hide the fact that there are still 4,2 billion individuals worldwide who remain offline – by circumstance or by choice (ITU, 2015). Calling the Internet a 21<sup>st</sup> century “necessity”, Barack Obama warns that the Internet is critical for individuals “to connect with today’s economy” (Superville, 2015). Moreover, as digital technologies increasingly pervade all aspects of our lives and progressively substitute offline services, the repercussions of *not engaging fully* with these technologies may become even more apparent. A recent study by the German Institute for Trust and Security on the Internet (DIVSI) on Internet participation cautions that we may be facing new socio-economic implications of digital inequality as those individuals who are able to leverage educational and economic opportunities available online stand to profit, while those who are not able to risk marginalization (2015). In order to meaningfully address this complex and societally relevant phenomenon, scholars and practitioners must gain a deeper understanding of *why* and *how* individuals differ in their adoption and use of ICT. To this end, technology adoption and use models can serve as a useful theoretical lens in uncovering the underlying individual and contextual drivers of digital inequality.

It is precisely at the interface of technology adoption research and digital inequality research that this cumulative thesis seeks to advance our knowledge. More specifically, this thesis aims to explore:

**Which mechanisms and factors influence why and how individuals use ICT in the context of digital inequality, and, in particular, what role do social influence, socio-cognitive processes, and socio-economic determinants play?**

This research question is particularly relevant for a number of reasons:

- Academic research on technology adoption and digital inequality has predominantly focused on uncovering the antecedents that drive the binary intention to (not) adopt and use a technology – the first-order effect of digital inequality (Eynon & Helsper, 2011; Hsieh, Rai, & Keil, 2011). As the phenomenon continues to evolve into a largely second-order

effect in developed countries, digital inequality scholars have called for a more nuanced understanding of why and how individuals differ in the way they appropriate ICT (Riggins & Dewan, 2005; Wei, Teo, Chan, & Tan, 2011). Similarly, technology adoption scholars have been challenged to move beyond the study of the antecedents of behavioral intention towards technology adoption and develop a better understanding of actual technology use and its outcomes (Burton-Jones & Grange, 2012; Straub & Burton-Jones, 2007). In this vein, this thesis strives to advance both digital inequality and technology adoption research by drawing on established as well as innovative technology adoption models to gain deeper insight into the mechanisms and factors behind disparate technology appropriation, and the implications thereof.

- In addition, extant research on social influence – a concept central to technology adoption and use (e.g. Tsai & Bagozzi, 2014), as well as digital inequality (e.g. Hsieh et al., 2011; Venkatesh & Sykes, 2013) – is characterized by heterogeneous construct definitions and a strong bias towards compliance-based interpretations (Bagozzi, 2007; Wang, Meister, & Gray, 2013), which undermine the conceptual integrity and explanatory power of the construct. This thesis aspires to strengthen the conceptual foundation of the research field by systematically reviewing and reconciling the myriad conceptualizations of the construct, and by providing guidelines for future research.
- Moreover, technology adoption and digital inequality research stand to benefit from a broader methodological foundation. Extant research relies heavily on survey-based techniques subject to common method bias, with a focus on behavioral intention rather than actual use (Benbasat & Barki, 2007). This thesis aims to provide more tangible insights on how individuals are using ICT and how they differ in their use by leveraging a multi-methodological approach that includes both qualitative research and internet-based data tracking of user behavior.
- Finally, despite the high societal relevance of technology non-adoption and digital inequality, there has been limited theoretically grounded, practitioner-oriented research on how to address the issue in general and second-order digital inequality in particular. Extant public policy continues to focus primarily on providing ICT access (e.g. Obama’s Connect Home initiative<sup>1</sup>) rather than pursuing a more integrated approach that includes targeted measures aimed towards promoting ICT appropriation (Kvasny & Keil, 2006). In light of

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<sup>1</sup> The Connect Home initiative aims to provide high-speed Internet connections and digital devices to more low-income families at lower cost (The White House, 2015).

this, this thesis strives to derive practical implications not just for academic research but also for practitioners, in particular public policy makers, on how to approach (second-order) digital inequality and bridge the gap between digitally advantaged and disadvantaged users.

The research question and goals laid out above serve as the guiding framework along which the four standalone papers that make up this cumulative thesis were conceived. The following paragraphs introduce each paper in brief.

This thesis starts out with a single-author paper that presents a systematic literature review of one of the most central concepts in technology adoption and digital inequality research: social influence (“*Social influence in technology adoption research: A literature review and future research agenda*”). Social influence has been shown to profoundly affect human behavior in general and technology adoption in particular (Asch, 1953; Taylor & Todd, 1995). Moreover, scholars have also found social influence to play an important role in the context of digital inequality (Agarwal et al., 2009; Hsieh et al., 2011; Venkatesh & Sykes, 2013). Over time, multiple distinct definitions and measures of social influence have been introduced to the field of technology adoption research, such as subjective norm, social capital, and group norms (Hsieh et al., 2011; Tsai & Bagozzi, 2014; Venkatesh et al., 2003). This has contributed to an increasingly fragmented landscape of constructs that challenges the conceptual integrity of the field and jeopardizes its further development. In this vein, this paper sets out to review how social influence has been conceptualized with regard to technology adoption and use. In so doing, this paper hopes to inform researchers’ understanding of the construct, reconcile its myriad conceptualizations, constructively challenge extant approaches, and provide a meaningful agenda for future research in this field. Building on the methodological frameworks put forth by Tranfield et al. (2003) and Webster and Watson (2002), I conduct a systematic review of the salient literature and uncover several interesting findings with important implications for social influence research in the field of technology adoption and use. First, extant interpretations of social influence are predominantly compliance-based and as such risk overlooking identification- and internalization-based effects, thereby undermining the potential explanatory power of the construct. Second, social influence is primarily studied at the individual level and with regard to non-social technologies, thereby precluding the impact of socially enriched environments, such as groups, and limiting our understanding to an incomplete set of technologies. Third, extant research methods rely heavily on cross-sectional, survey-based data and USA/China-centric samples, which jeopardizes the generalizability and predictive validity of the findings. Building upon these insights, this paper develops an



integrated perspective on social influence in technology adoption research which encourages scholars to pursue a multi-dimensional understanding of social influence at the interface of users, social referents, and technology.

Building on the theoretical foundation set out in the literature review, the second paper in this thesis develops a novel perspective on the socio-cognitive processes underlying technology use and non-use by leveraging a qualitative research approach. Entitled “*Mechanisms of engagement with, and disengagement from, Internet applications: A qualitative study of online job search*”, it was co-authored with Annika Reinartz. The paper aims to deepen our understanding of why people engage with, or disengage from, Internet applications and how factors such as social influence affect this process. As more and more aspects of people’s lives shift online, scholars have raised concerns that digitization is becoming a prerequisite to fully participate in society (Hargittai, 2003). Consequently, understanding what drives individuals to use – and, more importantly still – not to use digital technologies is now as pertinent as ever. This paper provides a new vantage to this societally relevant conversation by developing a process-based perspective on technology adoption and use on the basis of a semi-exploratory, qualitative case study of online job search in Germany. More specifically, this paper adopts a coping theoretical lens to expose the cognitive processes leading to engagement or disengagement with online job search applications, and explore the capital resources and contextual factors that influence this process, such as cultural capital, social capital, and trust. In contrast to most extant research in this field, this paper leverages a qualitative research approach (Eisenhardt, 1989; Strauss & Corbin, 1990) that is uniquely qualified to explore user behavior towards a technology as a dynamic and ongoing decision process, and account for the rich and complex nature of behavioral responses. This paper draws on a comprehensive foundation of qualitative data, including 182 pages of *in vivo* interview transcriptions, self-tests, on-site observations and archival data to develop a dynamic model of user (dis-)engagement. The findings highlight how instrumental specific capital resources are at different stages of the appraisal phase in determining whether an individual attains a favorable outcome, such as engagement, or an unfavorable one, such as disengagement and exit by exclusion. Moreover, the findings underscore that social capital in particular seems to play a more important role in engaging people with Internet applications than portrayed in previous studies (Hsieh et al., 2011). This not only endorses the importance of social influence with regard to technology adoption and digital inequality in general, but in particular validates the insight from the literature review (“*Social influence in technology adoption research: A*

*literature review and future research agenda*”) that conceptualizations of social influence extending beyond compliance-based effects are indispensable in capturing the full extent of the construct’s impact. Overall, the findings outlined in this paper entail important implications for IS research and public policy makers by identifying the mechanisms that lead to critical outcomes such as involuntary digital exclusion and by uncovering promising points of intervention.

The issue of digital exclusion serves as the focal point for the other main empirical study of this thesis, which complements the qualitative paper discussed previously by investigating how digital inequality manifests itself in the specific context of e-commerce and under consideration of socio-economic determinants using a unique, large-scale clickstream dataset. The paper – entitled “*Second-order digital inequality: A clickstream analysis of e-commerce use*” – was co-authored with Annika Reinartz, Andreas König, Lorenz Graf-Vlachy, and Jan Mammen. Second-order digital inequality refers to the phenomenon that certain individuals profit less from digital opportunities due to differences in their ability to effectively use ICT (DiMaggio & Hargittai, 2001). Scholars who have explored the implications of these differences in use have suggested that digitally disadvantaged individuals may suffer from real-life drawbacks such as an economic opportunity divide, resulting from their lesser ability to leverage Internet-based education, training, and employment opportunities (Mossberger, Tolbert, & Stansbury, 2003). This is particularly critical since the digitally disadvantaged are often also the socio-economically disadvantaged, meaning that economic inequality in the “offline” world might be further perpetuated in the “online” universe (Hargittai, 2003). In this context, e-commerce has recently emerged as a key area of opportunity creation within the digital inequality discussion given its potential benefits particularly for less privileged users. Scholars have hypothesized about a potential “e-commerce divide” (Riggins & Dewan, 2005, p. 20), yet have so far not validated its existence empirically. This paper addresses this research gap by extending digital inequality research to the realm of e-commerce and by introducing a novel theoretical perspective on effective – potentially economically beneficial – e-commerce use. This perspective encompasses two dimensions: (1) the extent to which an individual is able to leverage the *diversity of e-commerce platforms* available, such as flash sales and daily deals, and (2) the degree to which an individual uses *supporting e-commerce features*, such as price comparison or coupon sites, in conjunction with transactions. Building on technology acceptance theory and social psychology, the paper hypothesizes that socio-economically disadvantaged individuals are less likely than their socio-economically advantaged peers to use

e-commerce in a manner that promises economic gains. The hypotheses are tested on a large-scale sample of clickstream data tracking the online behavior of 2,819 US e-commerce users over six months in 2012. The results confirm that despite equal access, the socio-economically advantaged use e-commerce more effectively in both dimensions. The findings additionally reveal that – contrary to expectations – socio-economic status does not primarily affect *how much* individuals buy online, but rather *how* they search for and buy products. The implications are twofold: first, that digital inequality is nowadays primarily an issue of *how* individuals use the Internet, rather than *if*, and second, that at least with respect to e-commerce, the Internet does not seem to help compensate offline inequality and reduce economic disparities. Socio-economically advantaged, more digitally savvy individuals are more likely to leverage the opportunities available online, whereas socio-economically and digitally disadvantaged individuals do not seem to benefit equally.

In light of the societal implications of digital inequality, the thesis concludes with a practical perspective targeted at policy makers on how to bridge existing disparities. The paper – entitled “*Bridging digital inequality: What can public policy makers do to ensure equal benefit from online opportunities?*” – was co-authored with Annika Reinartz. This practice-oriented paper aims to convey some of the key insights on digital inequality from academic research – extant, as well as new insights developed in this thesis – to a practitioner audience, in particular public policy makers. This is particularly relevant because the root causes and manifestations of digital inequality can only be adequately preempted and addressed on a policy level, through such measures as better early-stage digital education and institutional support structures. Similar to other practitioner papers, this study adopts a top-down, functional perspective to inform policy makers about the phenomenon of digital inequality, potential domains for digital opportunities that merit special attention, and success factors in devising measures to bridge the gap. It highlights the critical importance of tackling the issue as more aspects of daily life shift online, marginalizing those individuals who are not able to leverage the ensuing digital opportunities. Six online domains are presented in which digital opportunities can be expected to have the greatest potential in decreasing social disparities, and which should be at the top of policy makers’ agendas in addressing digital inclusion. These are, more specifically, the domains of employment, e-government and public services, education, health, finance and insurance, and e-commerce. To illustrate the mechanisms and factors that inhibit individuals from leveraging digital opportunities and the role governmental institutions can play in this context, the paper outlines the main research insights from a case study of online job search in

Germany (drawing on the research presented in the paper “*Mechanisms of engagement with, and disengagement from, Internet applications: A qualitative study of online job search*”). Building upon these findings, the paper presents key success factors on how to bridge digital inequality. Policy makers should acknowledge the evolution of the digital inequality issue from an access-based to an appropriation-based issue (in developed countries) and direct their efforts – much more strongly than they are currently doing – towards nurturing effective use among the digitally disadvantaged and providing the appropriate support structures to that end. Specifically, measures aimed at reducing digital inequality should be embedded within institutional support structures, focus on skill-building and enablement, offer application-oriented training, and be targeted towards different user groups. Only by addressing digital inequality in a proactive and targeted manner do public policy makers have a chance of ensuring that everyone can benefit equally from online opportunities.

All the papers presented in this thesis have been submitted to peer-reviewed journals. Most notably, the paper “*Second-order digital inequality: The case of e-commerce*” was successfully published within the Proceedings of the International Conference on Information Systems (ICIS) 2014 (VHB Jourqual 3 rating: A). All other papers are currently under review: the literature review on social influence in technology adoption research is under review at the European Journal of Information Systems (EJIS); the paper “*Mechanisms of engagement with, and disengagement from, Internet applications: A qualitative study of online job search*” is under review at the Journal of the Association for Information Systems (JAIS); the paper “*Second-order digital inequality: A clickstream analysis of e-commerce use*”<sup>2</sup> is under review at the International Journal of Electronic Commerce (IJEC); and the practical perspective on digital inequality is currently under review at the Communications of the ACM (CACM).

Above and beyond the contributions of the individuals papers, the thesis as a whole provides substantial theoretical and methodological contributions to digital inequality research and technology adoption research. For digital inequality research, the empirical findings presented in this thesis first and foremost underscore that – contrary to claims that the issue would resolve itself by now – digital inequality continues to be a prevalent societal concern, even in countries with widespread Internet access. Furthermore, the findings validate that digital inequality has evolved into a second-order effect driven by differences in the way individuals appropriate ICT

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<sup>2</sup> The paper “Second-order digital inequality: A clickstream analysis of e-commerce use” is an adapted and expanded version of the earlier paper “Second-order digital inequality: The case of e-commerce”, which was published within the Proceedings of the International Conference on Information Systems (ICIS) 2014.

and the outcomes they achieve, as shown with respect to e-commerce and online job search applications. Moreover, the thesis advances the research field's theoretical understanding of the lesser known issues of appropriation and outcome implications by uncovering the underlying mechanisms and factors that influence how individuals engage with ICT.

This thesis contributes to technology adoption and use research by developing insights on how nuances in technology use manifest themselves and exploring the underlying mechanisms and factors that contribute to these differences. In contrast to most extant research in this field, this thesis adopts a process perspective to account for the dynamic nature of user (dis-)engagement, thereby yielding a more multi-faceted understanding of the mechanisms of technology use and non-use and the ensuing outcomes. It also extends the field's understanding of the role individual resources, such as cultural and social capital, can play at different stages of the engagement process and how they can contribute either to continued use or promote disengagement. In addition, it advances the field's theoretical understanding of social influence on technology adoption by reconciling its manifold conceptualizations and developing an integrated framework that provides promising vantage points for future research.

Methodologically, this thesis contributes to extant technology adoption and digital inequality research by leveraging a multi-methodological approach (quantitative, qualitative, and theoretical analysis) to generate novel insights. Through the use of large-scale clickstream data, this thesis uncovers far richer and more accurate insights on how individuals are actually using digital technologies than the field's more conventional survey-based techniques. This quantitative approach is complemented by qualitative research that allows the diverse underlying motivations of human behavioral responses to technology use and non-use to be captured in greater depth and richness. Rigorous theoretical analysis completes the spectrum and yields an integrated theoretical framework for future research on social influence in the field of technology adoption and use, as well as a novel conceptualization of e-commerce use.

Beyond contributions to academic research, this thesis also develops important insights for practitioners. It informs public policy makers – who must lead the way in proactively addressing and preempting digital inequality – what to watch out for in devising targeted policy interventions aimed at fostering digital inclusion. Managerial practice, in turn, may benefit by leveraging the insights to better target currently marginalized user groups.

All in all, this thesis serves to deepen academics' and practitioners' understanding on the causes and manifestations of the prevalent societal issue of digital inequality through the lens of

technology adoption research. In the following, the individual papers introduced in this preface are presented and rounded off by closing remarks that reiterate the key findings and contributions of the papers and this cumulative thesis as a whole.

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# **Social influence in technology adoption research: A literature review and future research agenda**

*Katharina Buhtz*

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## **Abstract**

Social influence has been shown to profoundly affect human behavior in general and technology adoption in particular. Over time, multiple distinct definitions and measures of social influence have been introduced to the field of technology adoption research, contributing to an increasingly fragmented landscape of constructs that challenges the conceptual integrity of the field and might jeopardize its further development. In this vein, this paper sets out to review how social influence has been conceptualized with regard to technology adoption. In so doing, this paper hopes to inform researchers' understanding of the construct, reconcile its myriad conceptualizations, constructively challenge extant approaches, and provide meaningful guidelines for future research. A systematic review of the salient literature uncovers that extant interpretations of social influence are 1) predominantly compliance-based and as such risk overlooking identification- and internalization-based effects; 2) primarily targeted at the individual level and non-social technologies, thereby precluding the impact of socially enriched environments; and 3) heavily reliant on cross-sectional, survey-based, and USA/China-centric samples, which jeopardizes the generalizability and predictive validity of the findings. Building upon these insights, this paper develops an integrated perspective on social influence in technology adoption research that encourages scholars to pursue a multi-dimensional understanding of social influence at the interface of users, social referents, and technology.

**Keywords:** social influence, subjective norm, technology adoption, technology acceptance model, information systems

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## **1. Introduction**

The impact of social influence on human behavior in general and information technology adoption in particular has been widely acknowledged (Asch, 1953; Triandis, 1980; Venkatesh et al., 2003). Social influence has originally been defined as the change in an individual's thoughts, feelings, attitudes, or behaviors that results from interaction with another individual or a group that is perceived to be similar, desirable, or expert (French & Raven, 1959; Kelman, 1958). Within information systems (IS) research, social influence has been incorporated as "the interpersonal considerations" of technology adoption and use (Chan et al., 2010, p. 525) in acknowledgment that such decisions are often done "collaboratively, or with an aim of how they fit in with, or affect, other people or group requisites" (Bagozzi, 2007, p. 247; Fulk, Schmitz, & Steinfield, 1990). As information and communication (ICT) technologies increasingly pervade all aspects of our lives, understanding what influences individuals to adopt and use these technologies continues to be relevant. With the emergence of ever more technologies, particularly social technologies, social influence may play an increasingly important role in determining which technology succeeds (Junglas, Goel, Abraham, & Ives, 2013; Tsai & Bagozzi, 2014). As such, it is imperative for researchers and practitioners alike to understand how social influence affects technology adoption.

A significant body of IS research has emerged that integrates the notion of social influence in its theoretical foundation and explores the relationship between social influence and technology adoption and use. Social influence has been incorporated into all the major theoretical models that serve as the bedrock of technology adoption research, such as the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model 2 (Venkatesh & Davis, 2000), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). Moreover, extant studies have found evidence that social influence plays a significant role in determining an individual's perceived usefulness of a technology (Wang & Chou, 2014; Williams, Slade, & Dwivedi, 2014) and their behavioral intention to adopt the technology (Chatterjee et al., 2015; Sun, Wang, Guo, & Peng, 2013).

However, this body of research is stratified. The interdisciplinary foundation of social influence within multiple research disciplines has led to a heterogeneous range of conceptualizations with a variety of labels and meanings. These include, for example, subjective norm, group norm, social identity, social capital, social network configuration, and critical mass (Venkatesh et al., 2003). Constructs like subjective norm view social influence as a perceived social pressure to

perform or not to perform a behavior (Fishbein & Ajzen, 1975). Others, like social identity, perceive social influence as a function of an individual's emotional and evaluative identification with a group (Tajfel, 1978). These starkly different interpretations of social influence pose a challenge for technology adoption research in developing a common understanding of the concept.

Moreover, while there is a theoretical consensus that social influence plays an important role in technology adoption, inconsistent empirical results undermine the explanatory power of the construct and question the validity of its present conceptualization. Many studies have found support for social influence on IT adoption (Chatterjee et al., 2015; Dickinger, Arami, & Meyer, 2008; Sykes, Venkatesh, & Gosain, 2009), while many others have not (Chan et al., 2010; Pavlou & Fygenson, 2006; Zhang, Prybutok, & Koh, 2006). Some studies found an effect for women, but not men (Venkatesh & Morris, 2000); for novice, but not experienced users (Karahanna, Straub, & Chervany, 1999); and for mandatory, but not voluntary adoption contexts (Venkatesh & Davis, 2000). A number of scholars have suggested that these inconclusive findings may result from a tendency to assume a limited conceptualization of social influence in technology adoption research (Bagozzi, 2007; Gallivan, Spitler, & Koufaris, 2005; Malhotra & Galletta, 2005). They note a strong bias toward providing normative explanations of technology adoption which do not reflect the wider societal context in which adoption occurs (Conner & Armitage, 1998; Sarker, Valacich, & Sarker, 2005; Wang et al., 2013).

As a result, notable IS scholars have expressed the need to better understand social influence itself and the relationship between social influence and technology adoption (Karahanna & Limayem, 2000; Legris, Ingham, & Collette, 2003; Mathieson, 1991). Notably, Bagozzi (2007) advocated that variables that account for group, social, and cultural behaviors and that go beyond normative influence should be added into the technology adoption paradigm. In response to these calls, a number of interesting developments in research have taken place that have added to a more pluralistic understanding of social influence in technology adoption research. For example, Dholakia, Bagozzi, and Pearo (2004) introduced group-level determinants – group norms and social identity – as antecedents to behavioral intention in their examination of virtual communities. Other researchers have explored technology adoption decisions at the group level to better account for social dynamics (Sarker & Valacich, 2010). Others still have theorized and empirically tested the notion of collective “we-intentions” with regard to technology adoption (Shen, Cheung, & Lee, 2013). While this increasing pluralism

promises to more fully capture the range of social impulses that govern technology adoption, it also contributes to an increasingly fragmented landscape of constructs that challenges the conceptual integrity of the field.

In this vein, I set out to conduct a systematic review of social influence in technology adoption research following the methodological frameworks put forth by Tranfield et al. (2003) and Webster and Watson (2002), with the aim of integrating the field's theoretical understanding of the concept and developing an agenda for future research. More specifically, this review first and foremost seeks to identify and reconcile the myriad conceptualizations of the construct, both established and emerging, that characterize its application in the field of technology adoption. In so doing, it aims to uncover theoretical intersections and illuminate key differences between the concepts. In addition to this conceptual level, this review also seeks to synthesize and expose the contextual and methodological implications of extant social influence research on technology adoption. Finally, the review aspires to develop an integrated framework of social influence on the basis of the emerging insights to serve as a meaningful guideline for future research.

Based on the in-depth review of 113 papers, a number of important findings and implications emerge for future social influence research in the field of technology adoption. First, despite the increasing pluralism in social influence conceptualizations, extant interpretations in technology adoption research remain heavily skewed towards compliance-based mechanisms. In so doing, scholars run the risk of missing the full relationship between social influence and technology adoption by “focusing on those aspects that fade over time, and not those that are likely to persist” (Wang et al., 2013, p. 301), such as internalization and identification. Second, a structural analysis reveals that social influence is overwhelmingly examined at the individual level of analysis. This selective focus on the individual precludes social dynamics to be captured that multilevel or collective perspectives could uncover. Third, extant research has primarily studied social influence with respect to non-social technologies. This raises questions regarding the predictive power of these conceptualizations towards social technologies, which are becoming increasingly important and have been shown to be subject to a larger range of social impulses. Fourth, moderating effects on social influence remain partially inconclusive, undermining the external validity of the construct. Finally, social influence research on technology adoption often does not differentiate among social referents and is heavily reliant on cross-sectional, survey-based, and USA/China-centric samples, which jeopardizes the generalizability and predictive validity of its findings. Building on these observations, I

develop a tripartite view of social influence centered on the interactions between users, social referents, and technology, which aims to serve as guiding framework for further research.

This review contributes to advancing our theoretical understanding of social influence on technology adoption by reconciling its manifold conceptualizations and developing an integrated framework that provides promising vantage points for future research. Most importantly, this review provides an important conceptual contribution by classifying and comparing extant social influence conceptualizations in the technology adoption domain according to their compliance, internalization, and identification effects, thereby providing unique insight into the distinct underlying cognitive processes the conceptualizations draw on and the implications thereof. In so doing, this review adds to previous review studies, which have focused on selected conceptualizations of social influence, such as subjective norm (Schepers & Wetzels, 2007), the underlying theoretical models of which social influence is a component, such as the Technology Acceptance Model (King & He, 2006; Oliveira & Martins, 2011; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010; Venkatesh et al., 2003), or adjacent literature domains, such as organizational and psychology research (Adler & Kwon, 2002; Borgatti & Foster, 2003; Cialdini & Goldstein, 2004). In addition, my study goes beyond purely conceptual analyses by incorporating a review and discussion of the methodological implications related to the operationalization of social influence in current research.

The remainder of this paper is organized as follows. The first section provides an overview of the concept of social influence and its application within the technology adoption domain. Next, the research methodology used to conduct this review is outlined. This is followed by the principal findings that emerged from the review of social influence in technology adoption research. Together with the findings, specific avenues for additional research are presented. Drawing these together, I develop an integrated framework of social influence and derive overarching propositions to guide future social influence research. The paper concludes with a synthesis of the key recommendations and a perspective on the potential limitations of this review.

## **2. The concept of social influence: A process view**

A first challenge in exploring the notion of social influence is establishing an understanding of what social influence is, given the myriad ways in which the concept has been studied, both as a cognitive process and a structural manifestation. As Cialdini, Reno, and Kallgren (1990, p. 1015) opine, the key challenge of social influence research is “definitional”. Beyond the well-

established consensus that individual behavior is profoundly affected by social factors (Asch, 1953; Fulk et al., 1990; Triandis, 1980), scholars have so far not agreed on a common approach to study the phenomenon. Social influence research is scattered across multiple domains, including sociology (Parsons 1951), psychology (Ajzen, 1991; Cialdini & Trost, 1998; French & Raven, 1959), organizational behavior (Pillutla & Chen, 1999), marketing (Algesheimer, Dholakia, & Herrmann, 2005), and economics (Akerlof & Kranton, 2000; Goyal, 2007), which undoubtedly contributes to its complexity and heterogeneity. Some disciplines, such as social psychology, predominantly explore social influence as a cognitive process driven by subjective beliefs, perceptions, and expectations (Morris, Hong, Chiu, & Liu, 2015). Other disciplines, such as economics, predominantly examine social influence in its structural manifestation as objective patterns of behavior in a social environment (Friedkin, 2004). Information systems research – by its nature an inherently interdisciplinary field – builds on both the cognitive and structural perspectives in exploring social influence (Agarwal et al., 2009; Friedkin & Johnsen, 1999). In order to lay the foundation for a theoretically grounded review of social influence, these two perspectives are detailed in the following.

Researchers who view social influence as a cognitive process distinguish between the three conceptually distinct processes of compliance, identification, and internalization (Kelman, 1958). This is outlined in Figure 1. *Compliance* is said to take place when an individual accepts influence because he hopes to achieve a favorable reaction from another person or group – “he adopts the induced behavior not because he believes in its content but because he expects to gain specific rewards or approval and avoid specific punishments or disapproval by conforming” (Kelman, 1958, p. 53). Compliance implies a change in behavior in response to social pressure without corresponding changes in beliefs or attitudes (Gallivan et al., 2005). *Identification* is said to occur when an individual adopts a behavior or opinion derived from another “because he wants to establish or maintain a satisfying self-defining relationship to another person or a group” (Kelman, 1958, p. 53). *Internalization* takes place when an individual integrates a referent’s belief into their own cognitive belief structure based on congruence in values.

Process (Kelman 1958)	Influence	Goal-orientation	Behavioral implication
Compliance	Normative	External reward	Conform
Identification		Self-maintenance / enrichment	Associate
Internalization	Informational	Knowledge	Accept

**Figure 1. Social influence processes (adapted from Burnkrant & Cousineau, 1975, p. 207)**

The processes defined by Kelman (1958) can be attributed to two distinct types of social influence – normative and informational. *Normative influence* is said to occur when individuals conform to the expectations of others, while *informational influence* is said to occur when individuals accept information as evidence of reality (Burnkrant & Cousineau, 1975; Deutsch & Gerard, 1955; Karahanna et al., 1999). For example, if a superior suggests that a particular technology is very useful, the focal individual may come to believe that it actually is useful, and in turn form an intention to use it – a case of informational influence. In contrast, if a superior suggests that he expects the focal individual to use a particular technology, the latter may do so to conform with the expectations but without altering his belief structure – a case of normative influence. Internalization is a form of informational influence while identification and compliance are forms of normative influence (Burnkrant & Cousineau, 1975). Within information systems research, these social influence types and processes provide the principal theoretical foundation for how social influence has been studied in technology acceptance models such as TPB/DTPB, TAM2, IDT, MPCU, and UTAUT<sup>3</sup> (Venkatesh et al., 2003).

Researchers assuming a structural perspective have studied social influence primarily through the lens of network externalities (Katz & Shapiro, 1985) and network theory (Borgatti & Foster, 2003). These theories infer social influence from the actual prevalence of a certain behavior in an individual's network and take into account the characteristics of that network. Network

<sup>3</sup> Theory of planned behavior (TPB) (Ajzen, 1991), Decomposed theory of planned behavior (DTPB) (Taylor & Todd, 1995b), Technology acceptance model 2 (TAM2) (Venkatesh & Davis, 2000), Innovation diffusion theory (IDT) (Rogers, 2003), Model of PC utilization (MPCU) (Thompson et al., 1991), Unified theory for acceptance of technology (UTAUT) (Venkatesh et al., 2003)



externalities, for instance, arise when an individual's utility of a specific behavior (e.g. using a technology) increases with prevalence of use within some reference group (Agarwal et al., 2009; Katz & Shapiro, 1985). For example, the more people use a social network such as Facebook, the greater the (social) value to the participating individuals and the higher the (social) cost of using an alternate social network. Network theory delves one level deeper and explores how the structure of an individual's network – defined by the “pattern and strengths of the interpersonal influences among the members of a group” (Friedkin & Johnsen, 1999, p. 1) – affects the individual's behaviour. This has been studied, for example, in relation to electronic trading systems (Montazemi, Siam, & Esfahanipour, 2008) and electronic health software (Venkatesh, Zhang, & Sykes, 2011).

Information systems scholars looking to integrate the structural perspective on social influence with the cognitive have posited that network externalities (and associated constructs) can exert both normative influence, through the process of compliance, as well as informational influence, through the process of internalization (Cho, 2011; Lou, Luo, & Strong, 2000). The underlying rationale is that as more and more individuals adopt a certain technology, the peer pressure to conform increases. Similarly, with increasing diffusion, potential adopters are also more likely to witness the technology in use, which may lead them to believe it is useful. These insights provide a basis upon which social influence models following the cognitive and structural perspectives can be compared.

For the purposes of this literature review, I build on Kelman's (1958) proposition that social influence operates through the processes of compliance, identification, and internalization. This cognitive process lens is particularly suited as a guiding framework for exploring how social influence has been studied in technology adoption research because it constitutes a theoretically grounded and collectively exhaustive structure according to which different conceptualizations of social influence can be meaningfully categorized. In so doing, the distinctions in the underlying cognitive motivations of each conceptualization can be exposed and the implications thereof made apparent.

An important consideration in my review of social influence is that I assume several boundary conditions. First, the review is limited to the field of technology adoption and use. The interdisciplinary nature of social influence and its widespread roots in multiple research domains invite expansive elaborations, yet this would be counterproductive to the quality of the review and unmanageable in terms of scope. The reader should be aware that additional

conceptualizations and applications of social influence exist in fields such as social psychology, which have not (yet) been incorporated into technology adoption research and are therefore not subject of this review. Furthermore, this paper pursues a construct-centric approach. This means that the conceptualization and operationalization of social influence lie at its core rather than the (underlying) technology acceptance models in the context of which the construct is explored<sup>4</sup>. Moreover, social influence needs to be clearly distinguished from a number of other similar behavioral antecedents in technology adoption literature. Notably, social influence should not be confused with environmental characteristics, such as incentives, financial resources and IT trainings (Brown, Dennis, & Venkatesh, 2010). Such environmental factors are accounted for as facilitating conditions in technology acceptance models (e.g. UTAUT) (Venkatesh et al., 2003). In the same vein, culture – be it organizational, national or a sub-dimension – is also conceptually distinct from social influence. Culture consists of the shared values and beliefs that exist within an organization or society and may certainly affect social influence, but can not be equated to social influence (Leidner & Kayworth, 2006; Morris et al., 2015).

### **3. Research methodology**

In order to explore how social influence has been studied in technology adoption research, I build on the methodological frameworks put forth by Tranfield et al. (2003), Webster and Watson (2002) and Leidner and Kayworth (2006). According to these frameworks, a structured approach to a literature review requires (1) pertinent criteria for the types of studies to be included in the search scope to ensure relevance, (2) a systematic search strategy to ensure replicability, and (3) a theoretically grounded, concept-centric framework for methodical coding and analysis. First, given the broad nature of the technology adoption and use research field and the frequent occurrence of social influence in many technology acceptance models such as TAM2, UTAUT, and TBP, a key criterion for the initial sample was that social influence was an integral constituent in the study and was mentioned in either the title, abstract or keywords. This approach was assumed to avoid an unmanageable sample of articles with limited value. In addition, only academic, peer-reviewed journal articles in English and from 2000 onwards were considered. These restrictions naturally constitute a trade-off between comprehensiveness on the one hand and relevance and replicability on the

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<sup>4</sup> For recent reviews of technology adoption models please refer to (King & He, 2006; Oliveira & Martins, 2011; Turner et al., 2010).

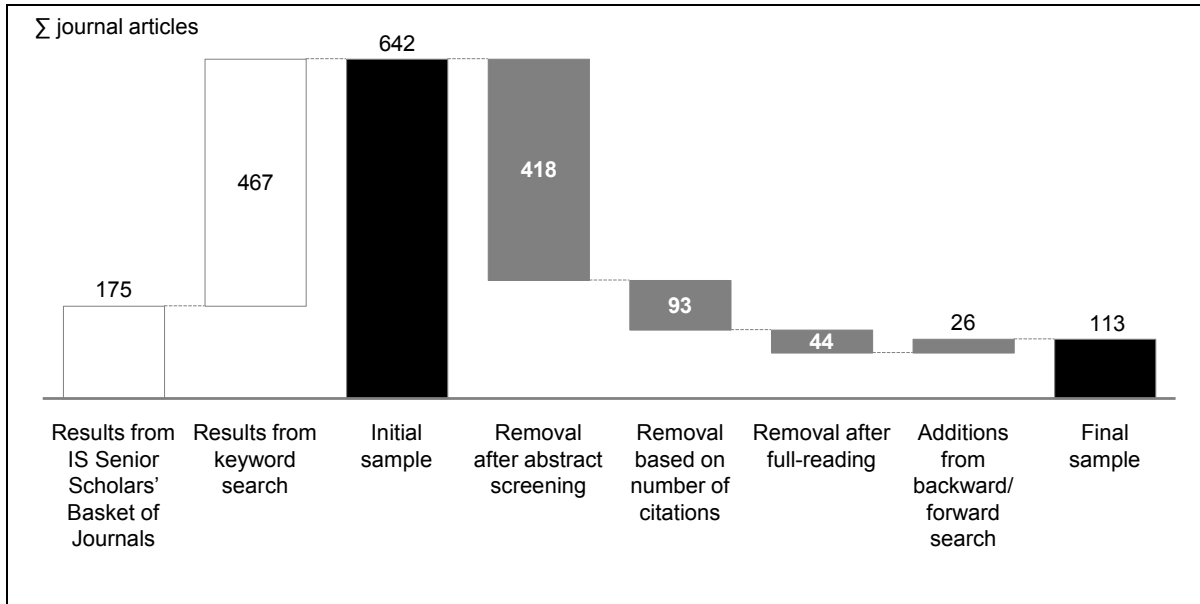
other, a limitation that must be taken into account when conducting a systematic literature review (Webster & Watson, 2002).

Second, a two-step approach was used to systematically identify the appropriate literature. In line with Li and Karahanna (2015) and Venkatesh et al. (2013), I started by reviewing papers published in the IS Senior Scholars' Basket of Journals<sup>5</sup> for relevant studies. Then, given the interdisciplinary nature of the IS field, I conducted a comprehensive database search of ABI/INFORM and Business Source Premier using the keywords "technology acceptance", "technology use", "technology adoption", in combination with "social", "social influence", "social norm", "subjective norm", and "social capital". Together, this resulted in a preliminary sample totaling 642 papers (Figure 2). Following an initial screening of the title and abstract, 418 papers were excluded. The large number of exclusions were primarily driven by studies relating to IT use and culture (e.g. Tan, Sutanto, Phang, & Gasimov, 2014), studies whose dependent variable was not technology adoption or use (e.g. Sarker, Ahuja, Sarker, & Kirkeby, 2011), and studies in which the word "social" was not related to social influence as an antecedent of adoption or use (e.g. Scott & Orlikowski, 2014). Similar to Bélanger and Carter (2012), the set of studies from the database search was further narrowed down by drawing on the number of Google Scholar citations and setting the bar at a minimum of 50<sup>6</sup> in order to improve the odds of academic relevance and research quality. This reduced the sample from 224 to 131 papers. Based on a full reading of these papers, a further 44 papers were excluded and an additional 26 papers added through forward and backward integration (Webster & Watson, 2002). In total, 113 journal articles were selected for in-depth coding.

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<sup>5</sup> The Senior Scholars' Basket of Journals encompasses the European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of the Association for Information Systems, Journal of Information Technology, Journal of Management Information Systems, Journal of Strategic Information Systems, and MIS Quarterly (AIS, 2011)

<sup>6</sup> This condition was only applied to papers published up to and including 2011. All papers from 2012 onwards were reviewed individually to prevent the timeframe since publication to act as a limiting factor on the number of citations. Moreover, a screening of the pre-2012 papers with less than 50 citations prior to removal from the sample confirmed – in line with Webster and Watson (2002) – that the majority applied extant constructs and methods from more highly cited papers rather than developing new ones, and thus did not add variance to the sample, only scope.



**Figure 2. Overview of article screening steps**

Third and finally, the 113 selected papers were coded systematically to gather insights on their conceptual and methodological approaches to studying social influence. A number of frameworks were drawn on to guide the coding approach. The social influence constructs were categorized in accordance with Deutsch and Gerard's (1955) nomological framework of types of influence (informational and normative) and Kelman's (1958) typology of social influence processes (compliance, internalization, identification). It should be noted that since social influence is often labeled using different terminology, such as social factors, social norms, and social pressure, the classification of the social influence constructs was undertaken not on the basis of the construct name itself but based on the review of the actual underlying measurement scale. In line with DeLone and McLean (1992) the level of analysis was categorized as individual, group, and organizational. In addition, a societal level was also included to account for cross-country studies on social influence. Conceptually, the following aspects were coded for: social influence conceptualization, theoretical basis, level of analysis, conceptualization of social reference group, and key findings. Methodologically, the following aspects were coded for: dependent variables, study setting, sample, focal technology, type of data, moderating effects and directional impact of social influence. Details of this coding are presented in Appendix B.

## **4. Findings and implications**

Several important insights about social influence research in technology adoption emerge from the review of the salient literature. First, a wide range of social influence conceptualizations are used in technology adoption research, with a significant skew towards compliance-based definitions. Second, a structural analysis reveals that social influence is overwhelmingly examined at the individual level of analysis. Third, social influence has been primarily studied with respect to non-social technologies. Fourth, moderating effects on social influence remain partially inconclusive. Finally, social influence research on technology adoption often does not differentiate among social referents and is heavily reliant on cross-sectional, survey-based, and USA/China-centric samples. I explore each of these issues in more depth in the following section, discuss the implications for technology adoption research, and provide specific avenues for further inquiry where relevant.

### **4.1 Conceptualization of social influence in technology adoption research**

Almost all technology acceptance models include, or have been extended to include, some form of social influence as an antecedent to the behavioral intention to adopt a technology. The review of the sampled literature reveals that the construct of social influence takes on many shapes and forms, including social norms, social capital, social network configuration, critical mass, social identity, group norms, and others. In the following section I draw on Kelman's (1958) typology of social influence processes to classify the various constructs according to the underlying process through which they operate – compliance, internalization, and identification – and discuss their application in technology adoption research. As becomes evident from Table 1, by far the most common interpretation of social influence used in technology adoption research is compliance-based, in the form of subjective norm. I outline the implications of this finding on the explanatory power of social influence in the context of technology adoption and provide vantage points for further research to help address this concern.

**Table 1. A taxonomy of social influence constructs in technology adoption research**

Construct	Theoretical basis	Definition	# papers by social influence process <sup>a,b</sup>		
			CPL	INT	ID
Subjective norm <sup>c</sup>	TRA (Fishbein & Ajzen, 1975), TPB (Ajzen, 1991), TAM2 (Venkatesh & Davis, 2000)	“A person’s perception that most people who are important to him think he should or should not perform the behavior in question” (Fishbein & Ajzen, 1975, p. 302)	70	18	
Social identity	Social identity theory (Tajfel, 1978)	“An individual’s identification with a group based on an understanding of the benefits that come with membership” (Dholakia et al., 2004)			13
Image	Innovation diffusion theory (IDT) (Rogers, 1995; Moore & Benbasat, 1991)	“The degree to which use of an innovation is perceived to enhance one’s status in one’s social system” (Moore & Benbasat, 1991, p. 195)			14
Group norms	Social identity theory and self-categorization theory (Turner, 1991)	“An understanding of, and a commitment by, the individual member to a set of goals, values, beliefs, and conventions shared with other group members” (Dholakia et al., 2004, p. 245)		11	
Support	Theory of interpersonal behavior (Thompson, Higgins, & Howell, 1991; Triandis, 1980)	“The individual’s internalization of the reference group’s subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations” (Thompson et al., 1991)		11	
Social network configuration	Social network theory (Granovetter, 1973)	The degree in which the structure of a network – defined by the “pattern and strengths of the interpersonal influences among the members of a group” (Friedkin & Johnsen, 1999, p. 1) – affects the behavioral intention to adopt a technology	9		
Critical mass	Critical mass theory (Markus, 1990), network externalities (Katz & Shapiro, 1985)	“The point at which enough individuals have adopted an innovation so that the innovation’s further rate of adoption becomes self-sustaining” (Rogers, 1995, p. 313)	20		
Social capital	Capital theory (Bourdieu, 1986; Coleman, 1990; Nahapiet & Ghoshal, 1998)	“Resources embedded in a social structure that are accessed and/or mobilized in purposive action” (Lin, 2001, p. 29). Nahapiet and Ghoshal (1998) classify social capital into three dimensions: structural, relational, and cognitive	5	6	4
Total number of papers <sup>1</sup>			93	70	30

a. Some articles are counted more than once because they contain multiple social influence constructs

b. CPL = compliance, INT = internalization, ID = identification

c. Also commonly referred to as social factors, social norms

#### ***4.1.1 Social influence as a process of compliance***

The literature review indicates that a compliance-based interpretation of social influence is the most common form studied. Of the 113 coded papers, 93 contain a compliance-based social influence definition as part of their overall social influence construct. The dominant conceptualization of social influence is in the form of subjective norm, defined as “the perceived social pressure to perform or not to perform the behavior” (Ajzen, 1991, p. 188). Theoretically grounded in TRA (Fishbein & Ajzen, 1975) and TPB (Ajzen, 1991), subjective norm is posited as a direct determinant of behavioral intention. The underlying rationale for this direct effect is that “people may choose to perform a behavior, even if they are not themselves favorable toward the behavior or its consequences, if they believe one or more important referents think they should, and they are sufficiently motivated to comply with the referents” (Venkatesh & Davis, 2000).

The reviewed literature indicates strong, but not completely consistent, positive support for this compliance effect. Around 70% of the relevant studies found a significant effect (e.g. Mardikyan, Beşiroğlu, & Uzmaya, 2012; Titah & Barki, 2009; Yang & Forney, 2013). While the large majority of papers (almost 90%) examined the direct effect of subjective norm on behavioral intention (Brown et al., 2010; Gao & Bai, 2014; Irani, Dwivedi, & Williams, 2009), a number of studies looked at its effect on actual use (Devaraj, Easley, & Crant, 2008; Liang, Wei, & Xue, 2010) and, in one case, even user satisfaction with the adoption decision (Chan et al., 2010). The direct effect of subjective norm has been studied both in work- (Neufeld, Dong, & Higgins, 2007) and non-work contexts (Lee, 2009), and with regard to a large range of different technologies, including telemedicine, enterprise software, and online shopping. In addition, whilst originally theorized to only hold in mandatory settings (Venkatesh et al., 2003), there is empirical evidence for positive compliance effects in voluntary settings (Kleijnen, Wetzels, & de Ruyter, 2004; Sun et al., 2013). Interestingly, in one case, a significant *negative* effect of subjective norm on behavioral intention is found (Sledgianowski & Kulviwat, 2009). This may be an outlier or an indication that compliance may, in voluntary (and non-work) settings, even act as a deterrent rather than a catalyst. Overall, the compliance effect of subjective norm was found to be significant in 65-75% of cases in each type of setting.

Notably, over a third of the reviewed studies feature a compliance-only social influence definition, which raises questions regarding the explanatory power of these conceptualizations. A closer look at the empirical results indicate that independent of setting (work/non-work,

voluntary/mandatory), only around 58% of papers found a significant social influence effect (e.g. Nysveen, Pedersen, & Thorbjørnsen, 2005b; Sun, Wang, Guo, & Peng, 2013; Venkatesh, Morris, Sykes, & Ackerman, 2004). Given that most theoretical models predicate that technology use is embedded in broader social context and inherently subject to social influences, this percentage seems rather low. The implication is either that social influence does not play such a key role after all, or that additional social influence processes exist that are not being captured by these compliance-based measures. The empirical inconsistency of compliance-based social influence measures certainly point to the presence of confounding or alternative effects which are not being accounted for in the present conceptualizations.

Critical mass, social network configuration and social capital are also theorized to operate via a compliance process. However, since these social influence conceptualizations also operate through additional processes, they are discussed separately under *4.1.4 Multi-processual conceptualizations of social influence*.

#### ***4.1.2 Social influence as a process of internalization***

In contrast to compliance-based definitions of social influence, internalization-based interpretations assume that an individual acts upon a social stimulus based on a congruence in values. The review of the literature indicates that a significant number of studies – in some form or other – incorporate such internalization effects of social influence in their technology acceptance models. Scholars have leveraged a variety of conceptualizations to this end, most notably the indirect effect of subjective norm, the notion of support and the construct of group norms.

IS scholars have most commonly studied internalization as an indirect effect of subjective norm on intention through perceived usefulness (as opposed to a direct compliance effect on intention) (Chen, Chen, & Chen, 2009; Hong & Kar, 2006; Wang & Chou, 2014). This approach was incorporated into TAM2<sup>7</sup> primarily as a reaction to the diminishing effects of (compliance-based) social influence over time, which Venkatesh and Morris (2000) attributed to individuals' tendencies to internalize others' opinions over time and focus on their own judgments. Accordingly, internalization, unlike compliance, is expected to ensue irrespective of whether the context of adoption is voluntary or mandatory. The reviewed literature supports

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<sup>7</sup> Subsequently superseded by the UTAUT, in which the indirect effect of subjective norm was dropped and replaced by a social influence construct that includes the notion of support (Venkatesh et al., 2003)



this hypothesis for the voluntary context (Dickinger et al., 2008; Williams et al., 2014), however only one of the reviewed studies also took place in a mandatory adoption context (Venkatesh & Davis, 2000). It found that the internalization effect was more pronounced in a voluntary than mandatory context whereas the opposite was true for the compliance effect. It would be interesting for scholars to further explore how the internalization effect manifests itself in mandatory adoption contexts and how it interacts with the compliance effect in these instances. Meanwhile, a number of studies found evidence of even more pronounced differences in voluntary contexts, with only the internalization effect of subjective norm able to be validated, while the compliance effect remained insignificant (Khalifa & Shen, 2008; J. Lu, Yao, & Yu, 2005; Yang, 2013). This highlights the importance of including non-compliance-based influence mechanisms when studying social influence – particularly in voluntary settings. Otherwise, scholars run the risk of missing the true relationship between social influence and technology adoption by “focusing on those aspects that fade over time, and not those that are likely to persist” (Wang et al., 2013, p. 301).

Interestingly, based on a closer look at how social influence is operationalized in the reviewed literature, the notion of support emerges as a distinct conceptualization of social influence. Support is understood to act as encouragement rather than expectation and hence cause an individual to internalize a reference group’s subjective culture rather than comply with it (Venkatesh et al., 2003). Grounded in the definition of social factors proposed by (Thompson et al., 1991) and later integrated into the social influence construct of the UTAUT model<sup>8</sup> (Venkatesh et al., 2003), support is typically used to complement compliance-based items rather than operationalized as a standalone construct<sup>9</sup> (e.g. Chatterjee et al., 2015; Gupta, Dasgupta, & Gupta, 2008). While this approach is empirically supported by sufficient levels of internal consistency within the reviewed sample, it unfortunately does not allow for the effects of internalization and compliance to be disentangled and studied individually. What is striking is that support has been measured disproportionately often within work settings, both with regard to mandatory (Al-Gahtani, 2004; Venkatesh & Zhang, 2010) and voluntary adoption

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<sup>8</sup> The UTAUT measures social influence based on a combination of two items related to subjective norm (Fishbein & Ajzen, 1975) and two items related to social factors (Thompson et al., 1991): (SN1) People who influence my behavior think that I should use the system, (SN2) People who are important to me think that I should use the system, (SF2) The senior management of this business has been helpful in the use of the system, (SF4) In general, the organization has supported the use of the system (Venkatesh et al., 2003)

<sup>9</sup> It is important to distinguish support as a form of social influence from support as a facilitating condition. The latter refers to objective factors in the environment that make an act easy to do, such as the provision of computer training and technical support in the context of technology acceptance (Thompson et al., 1991)

(Elie-Dit-Cosaque, Pallud, & Kalika, 2012; Liang et al., 2010). Since management and organizational support are quite tangible and easily measured, this is not surprising. Yet it would be interesting to extend the construct's application within the consumer sphere, where peer or family support have also been found to play influential roles in technology adoption (Hsieh et al., 2011; Thakur & Srivastava, 2013).

A recent, standalone representation of internalization processes on technology adoption has been in the form of group norms (Shen, Lee, Cheung, & Chen, 2010; Tsai & Bagozzi, 2014). Group norms aim to capture social influence determined by an individual's understanding of, and commitment by, shared values or goals with a group (Bagozzi & Lee, 2002). Consequently, group norms have been primarily studied with regard to group action and social technologies, where they have consistently been found to significantly predict behavioral intention (Dholakia et al., 2004; Shen et al., 2013). While most studies examine group norms from a variance perspective as an antecedent to behavioral intention (Gallivan et al., 2005) or attitude (Tsai & Bagozzi, 2014), one interesting stream of research has explored how group interaction affects the formation of group norms and group valence with regard to IT adoption (Sarker et al., 2005; Sarker & Valacich, 2010). Analogous to the findings on social identity, the empirical results of several studies suggest that group norms are a better predictor of adoption and use behavior than subjective norm when it comes to group-based technologies (Dholakia et al., 2004; Shen et al., 2013, 2010; Tsai & Bagozzi, 2014). As an increasing share of technologies become social and IT is increasingly used collaboratively, the aspect of group norms within technology adoption research may warrant additional attention.

#### ***4.1.3 Social influence as a process of identification***

Moreover, around 30 studies in the reviewed literature studied social influence as a process of identification. They predominantly drew on two types of conceptualizations to account for identification: constructs related to social identity (e.g. Papadopoulos, Stamati, & Nopparuch, 2013) and constructs related to image (e.g. Williams et al., 2014).

Anchored in social psychology research, social identity captures an individual's self-awareness of his or her membership in a group and the emotional and evaluative significance of this membership (Tajfel, 1978). Social identity is a more group-based interpretation of identification than image – Tajfel (1978) “desired to account for what he saw to be a fundamentally unique kind of social behavior distinct from intraindividual and interpersonal modes of behavior” (Bagozzi, 2007, p. 248). Bagozzi and Lee (2002) were one of the first

scholars to leverage social identity theory within the context of technology adoption to account for the effects of intergroup behavior on behavioral intention. In extant technology adoption research, social identity is typically measured as the perceived degree of overlap between an individual's personal identity and the identity of the group they associate with (Appendix A2). In most cases, social identity is hypothesized to have a direct effect on behavioral intention to adopt a technology (Bagozzi & Dholakia, 2006; Shen et al., 2013) or a mediated effect via an individuals' attitude (Faullant, Fuller, & Matzler, 2012; Tsai & Bagozzi, 2014). Almost all studies in the reviewed sample found a significant, positive effect (Chiu, Hsu, & Wang, 2006; Datta, 2011). Social identity was typically studied in conjunction with subjective norms and group norms in the context of models that aimed to explicitly test and validate all three social influence processes (Dholakia et al., 2004; Shen et al., 2010). Interestingly, a number of studies found evidence that social identity (and group norms) are better predictors of adoption and use behavior than subjective norm (Bagozzi & Dholakia, 2002; Shen et al., 2013, 2010; Tsai & Bagozzi, 2014). These studies coincide in that they examined technology adoption in the context of explicit group environments, such as virtual communities and social network-facilitated team collaboration. These findings support the notion that technology adoption is subject to different, distinct social influence processes and suggest that the explanatory power of identification-based processes may exceed those of compliance in group-based environments.

The other main conceptualization of the identification process is in the form of constructs related to image (Chan & Lu, 2004; Gounaris & Koritos, 2008). Within IS research, the notion of image is rooted within Innovation Diffusion Theory (Rogers, 2003) and TAM2, which integrates image into the original TAM to capture the identification effect of social influence (Venkatesh & Davis, 2000). According to TAM2, image is influenced by subjective norm and, in turn, influences perceived usefulness, while subjective norm is expected to also have a direct effect on perceived usefulness and behavioral intention. Closely-related constructs examine prestige associated with IT adoption or use (Chan & Lu, 2004; Riquelme & Rios, 2010), as well as social outcomes, understood to be the change in status that coincides with an adoption decision (Venkatesh & Brown, 2001). The impact of image and its related constructs have been primarily explored in relation to behavioral intention (Foon & Fah, 2011; Plouffe, Vandenbosch, & Hulland, 2001) and perceived usefulness (Chan & Lu, 2004; Lu et al., 2005; Williams et al., 2014). The empirical evidence predominantly supports the hypothesized relationships regarding image, while some interesting contingency effects emerge with regard

to subjective norm: a number of studies found sustained support for the effect of image on perceived usefulness, while subjective norms was only validated in mandatory, short-term settings (Venkatesh & Davis, 2000) and for potential adopters but not users (Chan & Lu, 2004). This suggests that technology adoption decisions are influenced by identification processes and that these operate independent of the contingency effects compliance-based processes are subject to such as voluntariness and experience.

#### ***4.1.4 Multi-processual conceptualizations of social influence***

In addition to the constructs discussed so far, which operate through only one distinct social influence process, there are also a number of social influence conceptualizations that are theorized to operate through multiple processes. These include critical mass/network externalities, social network configuration, and social capital.

20 of the reviewed studies explore social influence through the lens of (perceived) critical mass or (perceived) network externalities (Strader, Ramaswami, & Houle, 2007; Wattal, Racherla, & Mandviwalla, 2010)<sup>10</sup>. The two concepts are connected, as the presence of network externalities forms and influences the concept of critical mass, which in turn affects technology adoption (Hsu & Lu, 2004). The reviewed literature finds strong empirical support both for a direct effect of critical mass on behavioral intention (Cheng, 2011; Sledgianowski & Kulviwat, 2009) and an indirect effect, mediated by perceived usefulness (Lee, 2006; Rauniar, Rawski, Yang, & Johnson, 2014). The direct effect is theorized to operate as a normative, compliance-based process, whereby an individual's perception that a large number of his social referents are using a technology may influence technology adoption behavior without necessarily altering his internal belief structure (Cho, 2011). The indirect effect, in turn, is predicated on the notion that the intrinsic value of a technology with network externalities increases as more users adopt it, thereby affecting an individual's instrumental beliefs through internalization (Lou et al., 2000).

Interestingly, almost half the studies have incorporated perceived critical mass alongside subjective norm (e.g. Cheng, 2011; Kim, Jahng, & Lee, 2007). While all of these were able to validate direct or indirect critical mass effects, none (except for one) found significant support for a compliance-based subjective norm effect (Van Slyke, Ilie, Lou, & Stafford, 2007). Two

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<sup>10</sup> Technology adoption scholars speak of "perceived" critical mass since it is difficult to determine the actual critical mass threshold for a specific technology, but individuals may have a subjective perception thereof (Cho, 2011).

studies did, however, find evidence of internalization effects of subjective norm (Lee, 2006; Wang & Chou, 2014). This suggests that complementarities and interactions may exist between the subjective norm and perceived critical mass constructs. IS scholars may benefit from empirically testing these interactions in order to determine how the constructs are related to one another. In addition, a number of studies have incorporated aspects that are – conceptually and in their operationalization – very similar to the notion of critical mass under the labels ‘visibility’<sup>11</sup> (Gounaris & Koritos, 2008; Plouffe et al., 2001) and ‘descriptive norms’<sup>12</sup> (Foon & Fah, 2011; Yang & Forney, 2013; Yu, 2012).

Nine of the reviewed studies draw on social network configurations to study how social influence manifests itself on technology adoption. The configuration on an individual’s social network is theorized to affect the information and norms that flow through that network, which in turn impacts individual and collective behavior through internalization and compliance (Magni et al., 2013). Social network studies typically gauge social influence in terms of network size, centrality, and density (e.g. Guzzo, Ferri, & Grifoni, 2014; Sykes et al., 2009). A number of studies further differentiate by type of network, such as supportive versus informational (Bruque, Moyano, & Eisenberg, 2009) or intra- versus inter-team connections (Magni et al., 2013), while others differentiate by type of agency, such as cognitive versus relational (Montazemi et al., 2008) or absorptive versus disseminative capacity (Peng et al., 2014). Social network constructs have, for instance, successfully been used to study peer effects on digital inequality (Agarwal et al., 2009; Venkatesh & Sykes, 2013), e-health adoption (Peng et al., 2014; Venkatesh et al., 2011), and electronic trading systems (Montazemi et al., 2008). Almost all reviewed articles uncover significant, positive effects of network characteristics on adoption and use behavior (Bruque et al., 2009; Venkatesh & Sykes, 2013). Sykes and colleagues (2009, p. 390) even find evidence that “social network constructs [...] explain variance in system use over and above the predictors from the individual technology adoption perspective (i.e., behavioral intention and facilitating conditions)”.

Finally, a number of studies have also drawn on the concept of social capital. Theoretically grounded in capital theory, social capital refers to the “resources embedded in a social structure that are mobilized in purposive action” (Lin 2001), such as relatives, friends, and social

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11 For instance: “In my surroundings, I see the OGB website on many computers. The OGB website is commonly used in my surroundings.” (Wang & Chou, 2014)

12 For instance: “I would shop by mobile phone because of the proportion of my friends who do mobile shopping.” (Yang & Forney, 2013)

institutions. Social capital has attracted a lot of research attention with sociological and organizational research (Adler & Kwon, 2002; Baker, 1990; Borgatti & Foster, 2003), but has so far featured less prominently in technology adoption research. Thematically, social capital has been primarily studied in relation to digital inequality (Hsieh et al., 2011; Kvasny & Keil, 2006) and participation in virtual (knowledge sharing) communities (Chiu et al., 2006; Liao & Chou, 2012; Wasko & Faraj, 2005). Others have, for example, applied social capital in the context of tourism technology adoption (Lee, Cho, & Hwang, 2013). Conceptually, almost all of the reviewed studies leverage Nahapiet and Ghoshal's seminal definition of social capital as a combination of structural, relational, and cognitive dimensions<sup>13</sup> (1998). Through these dimensions, the social capital construct captures compliance, internalization and identification effects of social influence. Correspondingly, a number of studies have used social capital as a complement to subjective norm in order to attain a better representation of social influences (Lee et al., 2013; Liao & Chou, 2012) and found empirical support for both constructs. Extant research has validated both the construct's direct effect on use or intention to use (Chiu et al., 2006; Hsieh et al., 2011), as well as its indirect effect mediated by attitude (Liao & Chou, 2012) and instrumental beliefs (Lee et al., 2013).

#### ***4.1.5 Reflections on social influence conceptualizations in technology adoption research***

Reflecting on how social influence has been conceptualized in technology adoption research, a number of insights emerge. On the one hand, compliance-based definitions centered around the construct of subjective norm dominate. Over 80% of the reviewed papers include a compliance-based measurement of social influence and 30% do so exclusively, meaning that no other social influence process is accounted for. This observation can be explained by the research domain's theoretical foundation on technology acceptance models, such as TAM2, and their associated conceptualizations of social influence. Yet it also highlights the limitations of this theoretical reliance. The empirical inconsistency of compliance-based social influence effects and their liability to contingency effects underscore this finding.

On the other hand, a wide range of alternative conceptualizations of social influence exist that have so far not garnered as much attention in technology adoption research. This is mainly due

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<sup>13</sup> The structural dimension refers to the overall pattern of connections between individuals and is typically operationalized in form of network ties and network configuration (Wasko & Faraj, 2005). The relational dimension, in turn, captures the nature of a these connections and is typically operationalized as trust, identification, and reciprocity (Chiu et al., 2006). Finally, the cognitive dimension refers to resources "providing shared representations, interpretations, and systems of meaning" among individuals (Nahapiet & Ghoshal, 1998, p. 224) and operationalized as shared language and shared visions (Liao & Chou, 2012).

to the fact that these conceptualizations are not anchored in the established technology acceptance models that characterize this research stream, such as TAM or UTAUT. Structural constructs related to critical mass and social network configurations are fairly established in their own right, while others, like group norms and social identity, are more recent additions aiming to fill the void left by compliance-based constructs with regard to the wider social contexts of decision making (Bagozzi, 2007). The empirical support found for these alternative conceptualizations within the reviewed literature not only endorses their value but highlights the importance of including constructs that account for internalization and identification effects. Extant studies already show that the explanatory power of constructs like group norms and social identity exceed that of subjective norm in voluntary, group-based social technology environments (Shen et al., 2013; Tsai & Bagozzi, 2014). As technology adoption becomes increasingly consumer-driven and social, the importance of accounting for all types of social influence processes will only grow. Future IS research stands to benefit from leveraging and further developing the rich plethora of social influence conceptualizations already present in its midst.

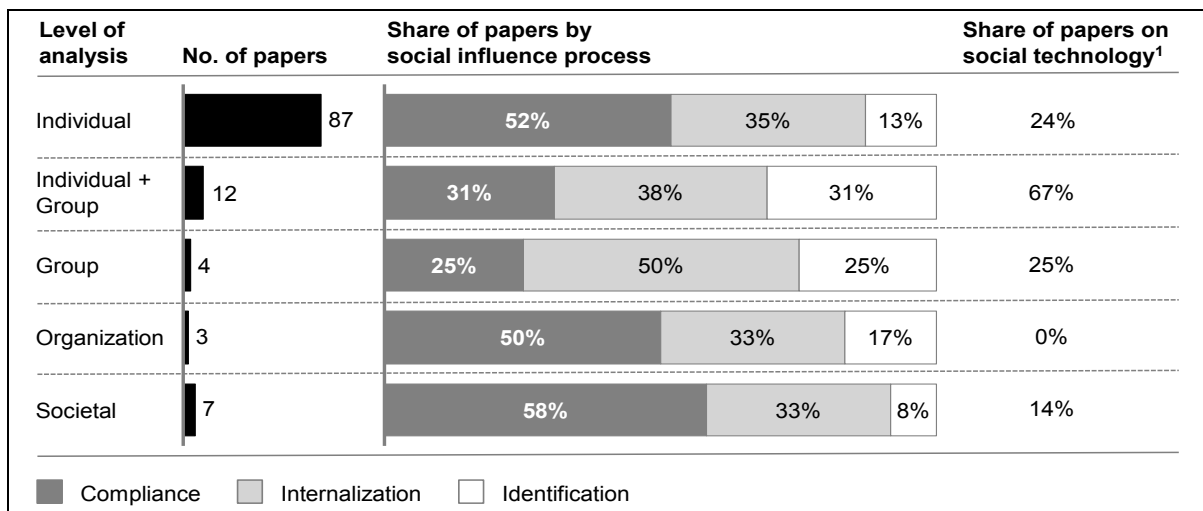
In doing so, scholars should remain aware of a number of methodological concerns that present themselves when trying to account for the multifaceted nature of social influence. Some scholars have noted a tendency for different social influence constructs to be “lumped together” under the term ‘social influence’ or ‘social norms,’ although the underlying motivations, decision rules, and social processes differ both conceptually and theoretically (Cho, 2011, p. 284; Kraut, Rice, Cool, & Fish, 1998). For instance, the social influence construct in the UTAUT – in an attempt to account for different social influence processes – is composed of subjective norm (Ajzen, 1991), social factors (Thompson et al., 1991), and image (Moore & Benbasat, 1991). It thereby combines items related to an individual’s perception that other people think he should use a new technology, the perception that others support his use of a new technology, and the perception that use of the technology is associated with a higher societal status. Accordingly, Van Raaij and Schepers (2008) have questioned how the combination of such disparate items can reflect a single psychometric construct. Similarly, concerns apply to the measurement of the direct (normative) and indirect (informational) effects of subjective norm and perceived critical mass, which are “conceptually distinct, but empirically entangled, types of social influences” (Kraut et al., 1998, p. 437) and typically operationalized using the same scale. Future research may benefit from disentangling such

mixed constructs and testing the subordinate constructs separately in order to properly establish if and how they are interrelated<sup>14</sup>.

## 4.2 Applications and contextual implications of social influence in technology adoption research

### 4.2.1 Structural view of social influence in technology adoption research

The literature reviewed in this paper was further categorized structurally by level of analysis, as presented in Appendix B1 and summarized in Figure 3. Behavioral and sociological research commonly differentiate between individual, group, organizational, and societal levels of analysis (DeLone & McLean, 1992; Klein, Dansereau, & Hall, 1994; Markus & Robey, 1988), evidence of all of which could be found in the reviewed literature. In addition, in some cases multiple levels of analysis could be observed, specifically combinations of individual and group levels of analysis. Three key insights emerge from the analysis presented in Figure 3. First, social influence on technology adoption has been overwhelmingly studied at the individual level, which is intriguing given the construct’s potential to capture collective behavioral dynamics. Second, internalization and identification effects of social influence seem feature most prominently at the group and individual & group level, presumably to account for non-compliance based collective processes. Third, social technologies interestingly seem to be studied primarily at a multilevel rather than a group level. These observations are detailed in the following and, building on that, specific avenues for further research are delineated.



**Figure 3. Levels of analysis by social influence process and focal technology**

<sup>1</sup> Refer to Appendix A1 for a classification of social and non-social technologies

<sup>14</sup> Cho (2011) provides a good example for how to do this based on subjective norm and perceived critical mass.



The large majority of the sampled research on social influence on technology adoption has been conducted at the individual level. This in itself is not a surprising finding, since technology adoption overall has traditionally been studied primarily at the individual level (Delone & McLean, 2003; Venkatesh et al., 2003). Behavioral research is inherently founded on individual attitudes and actions, and essentially all conventional behavioral antecedents in the IS field, such as perceived usefulness or perceived ease of use, are conceptualized at the individual level (Sarker et al., 2005). Even the social influence construct, meant to account for the social aspects of decision-making and arguably implicitly predicated on a group level or higher, is generally analyzed at the individual level from the perception of the focal individual, via indicators such as perceived social pressure or perceived overlap between individual and group norms (Sarker & Valacich, 2010). While this approach is very common and has established itself as the standard methodology, some IS scholars have criticized that it measures social influence in a unidirectional sense (Bagozzi, 2007) and relies solely on the perception of the focal individual without verifying the actual influence exerted from the social reference group (Burton-Jones & Gallivan, 2007).

In contrast, only 14 of the sampled papers explore social influence and technology adoption at a group, organizational or societal level. At the group level, some scholars have theorized about how to best measure technology adoption by groups and developed methodological individualist and non-reductionist models centered around the concept of group valence (Klein et al., 1994; Sarker et al., 2005; Sarker & Valacich, 2010). Others have investigated multi-group adoption – Plouffe et al. (2001), for instance, investigate the adoption of a smart card-based electronic payment system by different groups of consumers and retailers, and find that social influence processes differ by group. At the organizational level, scholars have examined the importance of social influence with regard to knowledge transfer in health information technology systems (Peng et al., 2014) as well as open source software adoption in SMEs (Macredie & Mijinyawa, 2011) and found significant, positive effects. At a societal level<sup>15</sup>, the sampled studies investigate either the applicability of technology acceptance models and social influence processes within non-western contexts (Al-Qeisi, Dennis, Hegazy, & Abbad, 2015; Datta, 2011) or undertake cross-cultural comparisons, generally between Western and Asian cultures (Choi & Geistfeld, 2004; Venkatesh & Zhang, 2010; Yang, Liu, & Zhou, 2012). Given

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<sup>15</sup> The sample of studies at the societal level is limited by the boundary condition that cultural values and dimensions (e.g. Hofstede, 1983) are not considered a social influence construct. For a review of culture in information systems research please refer to (Leidner & Kayworth, 2006).

the limited number of papers that fall into the non-individual category, it is difficult to formulate a conclusion regarding the social influence processes studied, although it is interesting to note that internalization seems to play a particularly prominent role at the group level of analysis.

Interestingly, a number of papers have also pursued a multilevel approach, most notably through the combination of individual and group levels of analysis. One stream of research pursuing this approach centers around the concept of “we-intention”, defined as “a collective intention rooted in a person’s self-conception as a member of a particular group [...], with action conceived as either the group acting as a unit or the person acting as an agent of, or with, the group” (Bagozzi, 2007). We-intentions have been studied extensively with regard to small-group based virtual communities (Bagozzi & Dholakia, 2006; Dholakia et al., 2004; Tsai & Bagozzi, 2014) and social-network facilitated teams (Shen et al., 2013, 2010). Another stream of research has focused on incorporating specific group-level characteristics into individual-level acceptance models, such as team climate (Liang et al., 2010), co-worker influence (Gallivan et al., 2005; Wang et al., 2013), and team internal closure (Magni et al., 2013). Noteworthy is the underlying social network method of data collection, as proposed by (Fulk, 1993), whereby co-worker/team variables were measured as an average of the actual responses of the social referents rather than from the perception of the focal individual. The review further suggests that multilevel research is more likely to account for the full range of social influence processes and explore them with regard to social technologies.

The current distribution of research presents ample opportunities for future research, particularly at macro levels of analysis. This is not to suggest that individual-level research should not be done, as interesting opportunities for future research exist. For instance, extant research within the IS field has so far yielded few insights on how normative and informational social influence processes interact with each other on the individual level in addition to their roles as cognitive predictors. Rather, this review aims to highlight the untapped potential in studying social influence on technology adoption at other levels of analysis that have so far garnered less scholarly attention.

At the group level, IS scholars should build on process theory and examine in more detail how group dynamics and interactions – manifestations of social influence – affect group attitudes toward technology adoption. Sarker and Valacich (2010) provide a good example of this type of research. They explore how majority opinion, intra-group conflict and opinion of high-status

individuals during a group exercise influence individual members' a priori attitudes toward the technology as well as the group's joint decision to adopt the technology. Furthermore, more group-level research is needed with regard to social technologies. It is surprising that only one of the group-level papers in the sample under review actually explores the adoption of a social technology. Within the management literature, the use of social technologies such as group decision support systems has garnered some attention but with a focus on performance rather than adoption (Pinsonneault, Barki, Gallupe, & Hoppen, 1999; Yoo & Alavi, 2001). IS scholars would do well to leverage some of these findings and explore them within the context of social technology adoption, which by its nature as a socially entrenched system is uniquely suited to be studied at the group level and is likely to be particularly susceptible to social influences.

At the organizational level, many of the same considerations hold. In order to study social influence phenomena within the context of organizational technology adoption, IS scholars may particularly benefit from integrating two streams of research: the structural perspective centered around social network configurations and innovation diffusion (e.g. Peng et al., 2015) with the behavioral perspective centered around issues such as peer influence, organizational culture and support that foster or impede adoption (Brown et al., 2010). In the adjacent IS field of knowledge management, social capital frameworks incorporating both structural (network ties) as well as relational and cognitive social capital (i.e. social trust, reciprocity, shared vision, peer influence) have successfully been used to study knowledge sharing in intra-organizational contexts (Adler & Kwon, 2002; Chow & Chan, 2008; Inkpen & Tsang, 2005). Initial studies on technology adoption confirm that, taken together, social network constructs can significantly enhance the understanding of system use over and above behavioral predictors (Sykes et al., 2009).

At the societal level, scholars should test the interaction of cultural values and social influence processes across a wider range of countries, most notably Middle Eastern, African and South American countries, to complement extant findings that have mostly focused on North America, Europe and Asia. In doing so, scholars should make sure to keep in mind the methodological issues related to the within-group homogeneity of aggregated individual data on a societal level (Gallivan & Benbunan-Fich, 2005; Klein et al., 1994).

Finally, a multilevel approach presents technology adoption researchers with the opportunity to study social influence in a more salient manner – one that extends beyond the focal individual's perception. This can be applied to all contexts and settings in which a defined

group or team exists, but is undoubtedly of most interest for social technologies. In addition, scholars should further validate and extend the measurement items developed by extant multilevel research in order to corroborate their validity and reliability. So far, for instance, the social network method has been primarily used to collect data on social referents' actual behaviors. It would be very interesting to extend this to include social referents' actual beliefs and perceptions on group norms as well, as partially implemented by (Gallivan et al., 2005). This would enable researchers to evaluate the degree of convergence between an individual's beliefs and behaviors and the social referents'.

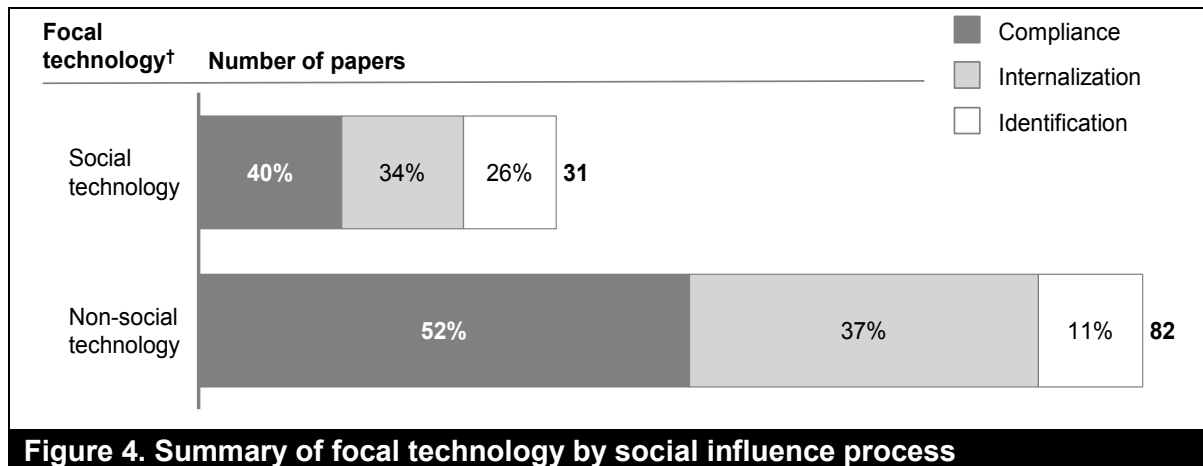
In summary, three interesting findings emerge from the structural review. First, social influence on technology adoption has been studied at various levels of analysis, but the large majority of studies have been at the individual level. Second, studies that extend beyond the individual level of analysis are more likely to incorporate social internalization and identification effects to account for non-compliance based group processes. Third, multilevel research emerges as an interesting avenue for studying social technologies. Future research stands to profit by engaging in more multilevel and group-level analysis of technology adoption in order to achieve more proximate representations of social influence, particularly when it comes to social technologies.

#### ***4.2.2 Social influence in relation to focal technology***

Social influence processes in technology adoption research have been studied in relation to a wide range of focal technologies. Within the organizational context, these include enterprise applications (e.g. procurement, knowledge management software), electronic trading systems and e-health software, among others (Kim et al., 2007; Venkatesh et al., 2011; Wang et al., 2013). Within the consumer sphere, studies explore acceptance and use of technologies such as mobile apps, e-commerce, and social media (Hong, Thong, Moon, & Tam, 2008; Junglas et al., 2013; Pavlou & Fygenson, 2006).

Classical technology acceptance models and their adaptations have been validated both in organizational and consumer contexts, yet have proven less useful for understanding technology use behavior where there is a strong community component (Baron, Patterson, & Harris, 2006). Scholars have attributed this phenomenon to the conceptualization of social influence (Faullant et al., 2012). They posit that particularly for social technologies, such as instant messaging for example, social influence has an enhanced role that goes beyond social pressure and comprises the user's need for relationships with others and with social groups

(Schau & Gilly, 2003). The underlying reasoning is that consumers co-create the value of social technologies and hence have to actively embrace and identify with the technology rather than just accept it (Faullant et al., 2012). Social technologies have been defined as “digital technologies used by people to interact socially and together to create, enhance, and exchange content” (Chui et al., 2012, p. 5) and include social hardware (traditional communication media), social software (computer-mediated media), and social media (social networking tools) (Alberghini, Cricelli, & Grimaldi, 2010).



**Figure 4. Summary of focal technology by social influence process**

† Refer to Appendix A1 for a classification of social and non-social technologies

A review of the present literature reveals significant differences between social and non-social technologies in terms of sample volume and manner in which social influence is conceptualized. Figure 4 shows the distribution of papers according to focal technology and social influence process. Of the 113 coded papers, only 31 explore social influence in the context of a social technology. They examine a range of social technologies in the consumer and organizational context, including blogs, messaging, virtual communities, knowledge sharing, and social media<sup>16</sup>. Li, Chau, and Lou (2005), for instance, find that social identity and critical mass have significant positive indirect effects (via perceived usefulness and perceived enjoyment) on the behavioral intention to adopt instant messaging. Similarly, Chiu et al. (2006) show that social capital – in the form of social interaction ties, trust, norm of reciprocity, identification, shared vision and shared language – significantly influences individuals' knowledge sharing in professional virtual communities.

Interestingly, a much higher proportion of the research on social technologies incorporates social influence processes relating to identification compared with research on non-social

<sup>16</sup> Please refer to Appendix A1 for a full categorization of social and non-social technologies found in the reviewed sample.

technologies. This includes aspects such as social identity (Bagozzi & Dholakia, 2002; Shen et al., 2013), social status (Nysveen, Pedersen, & Thorbjørnsen, 2005a; Yu, 2012), and relational commitment (Li et al., 2005), all of whom showed significant effects on behavioral intention or attitude. As Shen and colleagues (2013) explain in their hypothesis development, social identification constructs like social identity are expected to stimulate the collective acceptance and use of social technologies because users are motivated to assert their association with the group. In contrast, compliance-based social influence constructs – while contributing the largest share – can only be empirically validated in just over half the cases when the focal technology is a social technology (Bagozzi & Dholakia, 2002; Mutlu & Ergeneli, 2012; Nysveen et al., 2005b). These findings support Baron et al.'s (2006) proposition that when it comes to social technologies, an extended understanding of social influence is required that goes beyond social pressure.

With social technologies predicted to constitute an increasingly important part of organizational and consumer ICT infrastructure in future, they provide an attractive avenue for future research on technology adoption in socially enriched environments. Chui et al. (2012) report that social technologies already play an important role for organizations (e.g. 70% of companies use some form of social technology) and consumers (e.g. over 1.5 billion social networking users globally), and this role is only expected to increase as the potential within these technologies is tapped (e.g. 20-25% increase in knowledge worker productivity). Building on evidence that classical compliance-based technology acceptance models are not well suited for studying technology adoption in socially enriched environments (Baron et al., 2006), this provides a unique opportunity for IS scholars to review these models and particularly rethink the role of social influence therein. Specifically, IS research can contribute to a better understanding of social technology adoption and use by a) accounting for this trend in the choice of focal technology to study, b) acknowledging the social components of technology use in its paradigm, and c) by making sure to incorporate identification- and internalization-based processes when measuring the impact of social influence. For future users, their “relation to technology [will] impact on [their] whole way of life, including work and consumption” (Wilska, 2003, p. 459) and IS scholars must find a conceptualization of social influence that adequately accounts for this.

### 4.2.3 Moderating effects on social influence

The role of social influence on technology adoption and use is complex and subject to a wide range of contingent influences (Venkatesh et al., 2003). Inconsistent results regarding the relationship between social influence and behavioral intention have been attributed to moderating effects by gender, age, experience, voluntariness, and culture, among others (Srite & Karahanna, 2006; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Morris, 2000). The moderating effects found in the reviewed literature are summarized in Table 2 and detailed below.

<b>Table 2. Summary of moderating effects on social influence</b>			
<b>Moderator</b>	<b>Moderating effects on social influence tested<sup>a</sup></b>	<b>Significant moderating effects found<sup>a</sup></b>	<b>Observed contingent effect on social influence</b>
Gender	17	9	Greater for women
Experience	12	8	Decreases with experience
Age	10	4	Mixed results: network effects stronger for younger users, social norms greater for older users
Voluntariness	5	3	More/only significant in mandatory settings
Culture	7	5	More significant for Asian than Western cultures
Other	5	2	Moderators tested: education <sup>†</sup> , attitude (-), perceived behavioral control <sup>†</sup> , personality <sup>b</sup> , tech. anxiety (+)

a. Some articles are counted more than once because they contain multiple moderators

b. Significant and positive effect: conscientiousness, extraversion, agreeableness; insignificant effect: neuroticism, openness

† Moderating effect on social influence not significant

A number of studies have found that social influence is more salient for women than for men (Ilie, Van Slyke, Green, & Lou, 2005; Riquelme & Rios, 2010; Venkatesh et al., 2003; Venkatesh & Morris, 2000). This phenomenon builds on evidence from gender research which suggests that women are more sensitive to others' opinion (Becker, 1986; Eagly and Carli, 1981), more attentive towards interpersonal goals and success in interpersonal relationships than men (Carlson, 1971; Nysveen 2005), and value information from peers and friends more highly (Brown et al., 2010). Consequently, women are more likely to be swayed by social influence when it comes to technology acceptance decisions (Venkatesh & Morris, 2000). However, several studies testing for the moderating effect of gender have also found insignificant or inconclusive results (Al-Qeisi et al., 2015; Lee, 2009; Yu, 2012). These have been attributed to aspects like workplace settings, in which men and women with similar educational backgrounds and qualifications work (Gupta et al., 2008), and a low share of

women in the sample (White Baker, Al-Gahtani, & Hubona, 2007). All in all, these findings suggest that the effect of gender on social influence within the context of technology adoption is not necessarily as clear-cut as some studies propound.

The moderating effect of experience on social influence has also been extensively researched and consistently found to have negative relationship (Bagozzi & Dholakia, 2006; Venkatesh & Davis, 2000). The normative influence of compliance has been shown to attenuate over time as increasing technology experience provides a more instrumental (rather than social) basis for individual intention to use the system, to the point where social influence becomes insignificant with sustained usage (Venkatesh et al., 2003; Venkatesh & Morris, 2000). These findings have been tested and confirmed both in voluntary and mandatory settings, as well as in work and non-work settings (Fusilier & Durlabhji, 2005; Venkatesh et al., 2003). Internalization and identification effects, however, are expected to be independent of experience (e.g. Fulk, 1993).

The moderating effect of age on social influence has garnered less attention in technology adoption research and yielded inconclusive results. Prior research suggests that older respondents tend to place greater importance on affinitive behavior and subjective norms (Venkatesh et al., 2003). Some researchers found significant positive effects (Morris & Venkatesh, 2000; Yu, 2012), while others found significant negative effects – albeit contrary to expectations and attributed to the focal technology (blogs) (Wattal et al., 2010). In most cases, however, no significant effects could found (Brown et al., 2010; Mousa Jaradat & Al Rababaa, 2013; White Baker et al., 2007).

The impact of voluntariness on social influence has been subject to debate. Early technology adoption research, anchored in organizational settings with often mandatory system use, suggested that social influence becomes more salient when system use is perceived to be less voluntary (Hartwick & Barki, 1994). Venkatesh et al. (2003) even go as far as to posit that social influence only has a significant effect when use is mandated. However, these findings are based on the premise that social influence manifests itself in the form of compliance. In contrast, social influence in voluntary settings has been shown to operate indirectly by influencing perceptions about the technology via internalization and identification processes rather than normative beliefs (Liang et al., 2010). Moreover, with the expansion of the research field into the realm of consumer practice, in which virtually all technology adoption decisions are voluntary, voluntariness as a moderator has become increasingly obsolete while the large



number of significant results attests to the fact that social influence plays an important role in voluntary settings (Baron et al., 2006; Brown et al., 2010).

There is empirical support that culture moderates the effect of social influence on technology adoption (Choi & Geistfeld, 2004; Yang et al., 2012). Scholars studying culture generally draw on Hofstede's taxonomy of cultural values (1983). For instance, social influence seems to play a more important role in cultures that score highly on the collectivist dimension and a lesser role in individualistic cultures<sup>17</sup> (Choi & Geistfeld, 2004; Mutlu & Ergeneli, 2012). Moreover, social norms have also been found to be stronger determinants of intended behavior for individuals who espouse feminine and high uncertainty avoidance cultural values (Srite & Karahanna, 2006). Interestingly, the contingency effects of culture have almost exclusively been tested in connection with compliance-based definitions of social influence, via the direct effect of subjective norm on behavioral intention (e.g. Lee, 2009; McCoy, Everard, & Jones, 2005). This one-sided perspective may result in an inflated contingency effect since compliance is expected to be particularly pronounced in cultures that, for example, score highly on the collectivism scale. The effect may – or may not – be different when looking at complementary social influence processes such as internalization and identification. As such, it would be interesting for technology adoption research to explore the impact of these distinct social influence processes across cultures in a more nuanced manner, as finer-grained differences may emerge.

Lastly, a number of other moderators on social influence have also been tested, such as education (White Baker et al., 2007), attitude and perceived behavioral control (Fusilier & Durlabhji, 2005), personality (Devaraj et al., 2008) and technology anxiety (Yang & Forney, 2013). In most cases, no significant moderating effect could be found, except for attitude and technology anxiety.

Overall, the review of moderating effects on social influence leads to a somewhat inconclusive picture. Generally, social influence seems to more salient for women, in collectivist cultures and mandatory settings, and particularly in the early stages of experience when an individual's opinions are relatively ill-informed. Yet for all these findings conflicting ones also exist. In

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<sup>17</sup> The dimension "individualism-collectivism" designates the preference for a social framework where individuals take care of themselves (individualism) as opposed to collectivism, where individuals expect the group to take care of them in exchange for their loyalty (Hofstede, 1983). Collectivist and individualist societies differ in the extent to which "we-"/"I-consciousness" prevail and the importance of group opinions in one's decision-making and behavior. Thus, the importance and impact of social influence can be expected to vary significantly from one culture to another and in particular between individualist and collectivist cultures.

addition, of the 113 coded papers only 29 tested any moderating effects at all and in these, around 40% of the hypothesized relationships proved insignificant. The inconclusive nature and large share of insignificant findings suggest that there is the potential for more research on contingent factors. In particular technology-related affective factors like technology anxiety, technology readiness and information overload warrant further research (e.g. Datta, 2011; Yang & Forney, 2013). Importantly, IS scholars should account for the nature of the social influence process (compliance, internalization or identification) when testing for moderating effects, as this can lead to otherwise confounding effects as seen in the case of voluntariness. Furthermore, while voluntary and mandatory settings have already received a lot of attention, future research would benefit from exploring how other environmental factors such as work-/non-work settings moderate social influence processes on technology adoption.

### **4.3 Methodological considerations**

In reviewing the technology adoption literature on social influence, methodological characteristics relating to the sample and research approach were also explored. In particular, the specification of the social reference group, the data collection method (e.g. survey, interviews, use logs), the national or cultural origin of the respondents, and the study design (i.e. cross-sectional, longitudinal) were reviewed. A number of interesting findings emerge, as discussed below. Notably, a significant share of studies do not explicitly specify a social reference group despite evidence that social influence varies considerably depending on the referent. Further, a large majority of studies build on self-reported, survey-based behavioral data which is subject to critical methodological limitations. Moreover, social influence research has heavily relied on US and Chinese samples as proxies for Western and Asian cultures respectively. Finally, cross-sectional studies dominate while longitudinal investigations into the sustained effects of social influence over time are rare. Detailed results are included in Appendix B2.

#### ***4.3.1 Specification of social reference group***

Social influence is a relational construct dependent on the social reference group at its basis. Social reference groups are defined as the “(1) groups which serve as comparison points; (2) groups to which a person aspires; and (3) groups whose perspectives are assumed by the actor” (Shibutani 1955). The referent influence may be interpersonal (e.g. family, friends, colleagues, superiors) or external (e.g. mass media, expert opinions), and social influence may manifest

itself through overt statements, vicarious learning, interpretations of events, social definitions of rationality, and provisions of standards (Bhattacharjee, 2000; Fulk, 1993; Kim et al., 2007). While attitudes, which serve as one of main pillars of technology acceptance models, are largely time-invariant predispositions (Zimbardo, 1970), social influences represent the social understanding of a technological artifact by a defined group of people and vary from referent to referent (Chatterjee et al., 2015; Mathieson, 1991). As such, an individual that moves from one social context to another is likely to be subject to different social influences.

<b>Table 3. Social reference group specification in technology adoption research</b>		
<b>Social referents</b>	<b>Item wording (examples)</b>	<b>Sources (examples)</b>
Unspecified social referents within a single variable	People who are important to me/ people who influence me/ people whose opinion I value/... think that I should use the system (multiple items)	Pavlou & Fygenson, 2006; Titah & Barki, 2009; Wang & Chou, 2014
Specified social referents within a single variable	My supervisor/my colleagues/my friends/my family/ my relatives/... think that I should use the system (multiple items)	Chatterjee et al., 2015; Hsu & Lu, 2004; Srite & Karahanna, 2006
Specified social referents across multiple variables	<p><i>Construct A: Interpersonal influence (INI)</i></p> <ol style="list-style-type: none"> <li>1. My supervisor thinks that I should use the system</li> <li>2. My colleagues think that I should use the system</li> <li>3. My friends think that I should use the system</li> </ol> <p><i>Construct B: External influence (EXI)</i></p> <ol style="list-style-type: none"> <li>1. I see news reports that using the system is good</li> <li>2. Expert opinions depict a positive sentiment for using the system</li> <li>3. Mass media reports convince me to use the system</li> </ol>	Brown et al., 2010; Cheng, 2011; Hsieh et al., 2011; Lewis, Agarwal, & Sambamurthy, 2003

Based on the review of the salient literature on social influence in technology adoption research, three clusters of social reference group specification emerge: 1) unspecified social referents within a single variable; 2) specified social referents within a single variable; and 3) specified social referents across multiple variables (Table 3). Interestingly, a large share of social influence research in IS falls into cluster one, in that social referents are typically left unspecified and only referred to as “people”. In the present sample, this was the case for 52 of the 113 reviewed papers. Partly, this approach can be traced back to the original foundation and operationalization of the subjective norm construct within TRA/TPB (Ajzen, 1991). Other social influence constructs such as image and critical mass have also operationalized social referents in a similar manner at times (Gounaris & Koritos, 2008; Ilie et al., 2005). To some extent of course, the social referents may be deduced from the study context and no explicit need to specify them may exist. Aboelmaged (2010), for instance, explores e-procurement adoption in a work-context. The focal technology and workplace setting delineate the

theoretical social reference group – i.e. workplace peers, superiors, subordinates and organization. Nevertheless, differences may exist between these social referents, as peers may think differently about the new technology than superiors for example. This may result in confounding effects when left unspecified.

The second cluster encompasses studies that specify one or multiple social referents within a single social influence variable (e.g. Liang, Wei, & Xue, 2010; Neufeld, Dong, & Higgins, 2007). In cases with one specified social referent, convergent validity and internal consistency of the measurement variable tend to be very high, with a Cronbach's  $\alpha$  exceeding 0.9 (e.g. Lu & Hsiao, 2007). In cases with multiple social referents, the underlying assumption is that the discrete social referents will have a similar directional impact. This highlights the need for caution when using single variables with multiple social referents, as the convergent validity and internal reliability of the measurement variable may be undermined. A screening of the literature indicates that this is a valid concern, with Cronbach's  $\alpha$  around 0.70 in some instances (Foon & Fah, 2011).

The final cluster comprises studies that operationalize distinct social referents as discrete variables. Hsieh et al. (2011), for instance, differentiate between social capital from family, relatives, peers and friends on the one hand and support from acquaintances on the other. Notably, their results indicate that the former has a significant, positive social influence, while the latter remained insignificant. Similarly, Srite and Karahanna (2006) posit that differences in the salient social reference groups that comprised subjective norm in their research study (professors vs. relatives) was the determining factor why they found a significant social influence in one of their studies but not the other. Moreover, Wang and colleagues (2013, p. 299) found a “fine-grained pattern of influence across different social groups”: strong support for bottom-up social influence across hierarchical levels, limited support for peer-level influence within levels, and no support for top-down influence. These examples offer a strong indication that not all social referents will have the same influencing effect on the focal individual and illustrate the value of clearly specifying and operationalizing distinct social reference groups.

In summary, IS researchers stand to profit from a more specific definition of social referents when measuring social influence. Extant studies range from having virtually no specification at all (“people”) to featuring discrete variables for distinct social referents. The heterogeneous findings of the latter demonstrate that the nature and extent of social influence can vary from

referent to referent. Consequently, a differentiated conceptualization and operationalization of social referents is likely to foster a more nuanced understanding of how social influence impacts technology adoption and use. To do so, scholars may benefit from leveraging methodological approaches such as the key informant method (Seidler, 1974) or a roster-based socio-metric approach (Wasserman & Faust, 1994).

#### **4.3.2 Data collection method**

The large majority of studies in the reviewed sample build on self-reported, survey-based behavioral data. Of the 113 reviewed papers, 94 measured social influence using a survey item filled out by the subject. This means that social influence is typically operationalized from the focal individual's perception of referent others' beliefs and behaviors, rather than on the basis of the actual beliefs or observed actions of referent others (Agarwal et al., 2009). Such an approach, while common, is subject to methodological limitations in the form of common method bias, which can undermine the validity of empirical results and lead to misleading conclusions<sup>18</sup>. Subjective norm, for instance, is commonly queried using the following items: "People who influence my behavior think that I should use...", "People who are important to me think that I should use..." (Taylor & Todd, 1995a). While compliance-based influences are undoubtedly the easiest to measure in this manner, other social influence aspects such as group norms and social identity are significantly more abstract and harder to self-report accurately. The issue with self-reporting behavioral attitudes and beliefs is that these may be skewed by a whole range of factors, from social desirability to transient mood state, and not reflect the focal individual's true attitudes and beliefs (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In addition, behavioral antecedents to use, such as social influence, are often measured retrospectively, following the adoption of a technology. This makes it hard to pinpoint the focal individual's beliefs during the actual adoption decision-making process (Venkatesh et al., 2003).

Some IS scholars have tried to address this problem by using a social information processing (SIP) lens and methodology to isolate the impact of others' actions on one's own (Fulk et al., 1990; Rice, Grant, Schmitz, & Torobin, 1990). For example, rather than asking subjects what

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<sup>18</sup> Common method bias relates to "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003, p. 1). Common method bias can stem from specific items in a construct, scale type, response format and general context of the data collection (Fiske, 1982) and most commonly afflicts survey-based research. Typical biases include common rater effects, item characteristics effects, item context effects and measurement context effects (Podsakoff et al., 2003).

they thought their co-workers and supervisors believed, the researchers collected data directly from the salient referent group and evaluated the coworkers' actual beliefs and behaviors in order to establish the degree of convergence with the subject's (Gallivan et al., 2005; Rice & Aydin, 1991). Others have drawn on data logs of social referents' actual use of the technology to infer identification and internalization effects on the focal individual's use (Wang et al., 2013). A better and more objective representation of social influence is theorized to result from such an operationalization. For this effect to be validated, a comparison study may be useful. At the same time, this method also has its drawbacks since inferring social influence from use patterns does not allow for distinctions between types of social influence.

In summary, scholars studying social influence on technology adoption should consider and justify their choice of data collection method. Self-reported, survey-based measures are most common, yet subject to methodological limitations. Alternatively, scholars should consider employing direct measures of social referents' beliefs and behaviors where meaningful – for instance when determining group norms or critical mass. Moreover, using self-reported surveys does not preclude from also gathering the data directly, or vice versa. Hence, scholars may choose to employ both methods concurrently and use the insights to complement or contrast the respective findings.

#### ***4.3.3 Respondent origin***

A large proportion of technology adoption research is based on US- and China-centric samples. In the literature sample under review in this paper, over 60% of papers draw on US and Chinese respondents. The remainder draws on a scattering of European and other Asian countries. As discussed previously, cultural background can have a significant effect on social influence and subsequent technology adoption and use (Straub, Loch, Evaristo, Karahanna, & Srite, 2002). It is encouraging to see that China-based research plays an increasingly prominent role and provides a counterweight to the long-existent cultural hegemony of US-based research on technology adoption (McCoy, Galletta, & King, 2007). At the same time, however, it seems the research field has shifted from the dominance of one to the dominance of two countries. This can become problematic at the point where US- and China-based samples become proxies for Western and Asian cultures and are positioned or understood as such.

While the impact of culture on social influence and technology adoption is particularly visible when contrasting starkly different cultures like the US and China, it would be amiss to position these results as representative for other countries in the same region (McCoy et al., 2007). For

instance, when comparing China and South Korea using Hofstede's cultural dimensions, striking differences can be observed. China scores significantly higher on power distance and masculinity, while Korea strongly outweighs China in terms of uncertainty avoidance (Hofstede, 2015). Other direct neighbors such as India or Japan exhibit other scores still. Therefore, there is a need for caution in generalizing findings on the impact of social influence on technology adoption across cultures.

More studies are needed that provide a nuanced understanding of social influence processes on technology adoption across a broader range of cultures. Extant research confirms that social influence varies by culture yet unfortunately there are still many white spots on the map and room for a more fine-grained understanding. Particularly technologically emergent markets such as Africa, Middle East, South America and parts of Asia, in which penetration rates are much lower than in the US, Europe or China, provide a fertile ground for exploring the effects of social influence on technology uptake.

#### **4.3.4 Study design**

One last methodological aspect to highlight is the study design. The review of the literature reveals that 93 of the 113 coded papers employed a cross-sectional study design. Only a handful studied social influence on technology adoption and use from a longitudinal perspective (e.g. Pavlou & Fygenson, 2006; Venkatesh et al., 2011). Longitudinal studies typically examine the impact of social influence at different stages of the adoption process, such as pre-adoption, adoption and use, and with respect to post-adoption outcomes such as performance, satisfaction or economic benefit (Peng et al., 2014; Venkatesh & Sykes, 2013). The findings suggest that the effects of social influence may differ at different points in time, being more salient at the early stages of adoption and less so later on, as the user gains experience. This effect holds true at least for normative, compliance-based influence mechanisms, which are expected to attenuate over time to the point where they become insignificant with sustained usage (Venkatesh et al., 2003). Internalization and identification effects, however, are expected to be time-invariant (e.g. Fulk, 1993). This review is not aware of any studies that have explicitly tested and compared the longitudinal effects of distinct social influence processes and thus encourages IS scholars to do so. Understanding the sustained effects of social influence over time is of great interest, particularly with respect to understanding continued technology use. Technology adoption research has often predominantly centered on the initial adoption decision, yet arguably continued use – and the factors contributing thereto – warrant just as

much research attention. To this end, longitudinal study designs may be more useful than cross-sectional ones.

In summary, the review of the salient literature has yielded a plethora of findings encompassing how social influence is being conceptualized, at what level it's being analyzed and what its contingency effects are, as well as how it is being operationalized and studied. Throughout the text, the implications of the findings are discussed and specific impulses for further research are provided. In the following, this paper aims to move beyond these individual ideas by providing a holistic perspective on how social influence research in IS may move forward and developing a framework to guide future research in this development.

### **5. Moving forward: Toward an integrated perspective of social influence in technology adoption research**

The review reveals that technology adoption research on social influence is characterized by considerable variation in the types of concepts studied and evidence of multiple social influence processes operating under different conditions. Two central implications emerge from these findings. First, IS scholars should reject a monolithic conceptualization or one-sided theorization of social influence processes (Cho, 2011; Merton & Sztompka, 1996). The review shows that multiple theoretical routes of social influence can coexist and complement each other. A normative, compliance-based perspective on social influence has characterized early technology adoption research and is still the dominant conceptualization today, yet IS scholars are increasingly incorporating additional social influence processes and conceptualizations in their research and thus introducing some of the interdisciplinary pluralism in our understanding of social influence to the field of technology adoption and use. This contributes to a richer understanding of social influence. Therefore, rather than suggest the development of a single perspective on social influence in technology adoption research, this paper echoes the sentiment expressed by Scott (1987, p. 493) that “further improvement and growth...is dependent upon [scholars] dealing more explicitly with these differences”. In this vein, I encourage future IS researchers to adopt a multi-theoretical approach and to actively elaborate on the distinct theoretical mechanisms by which different social influence processes can affect technology adoption and use.

Second, the review of the salient literature further suggests that scholars not only need to consider how to conceptualize social influence but also fundamentally challenge how social

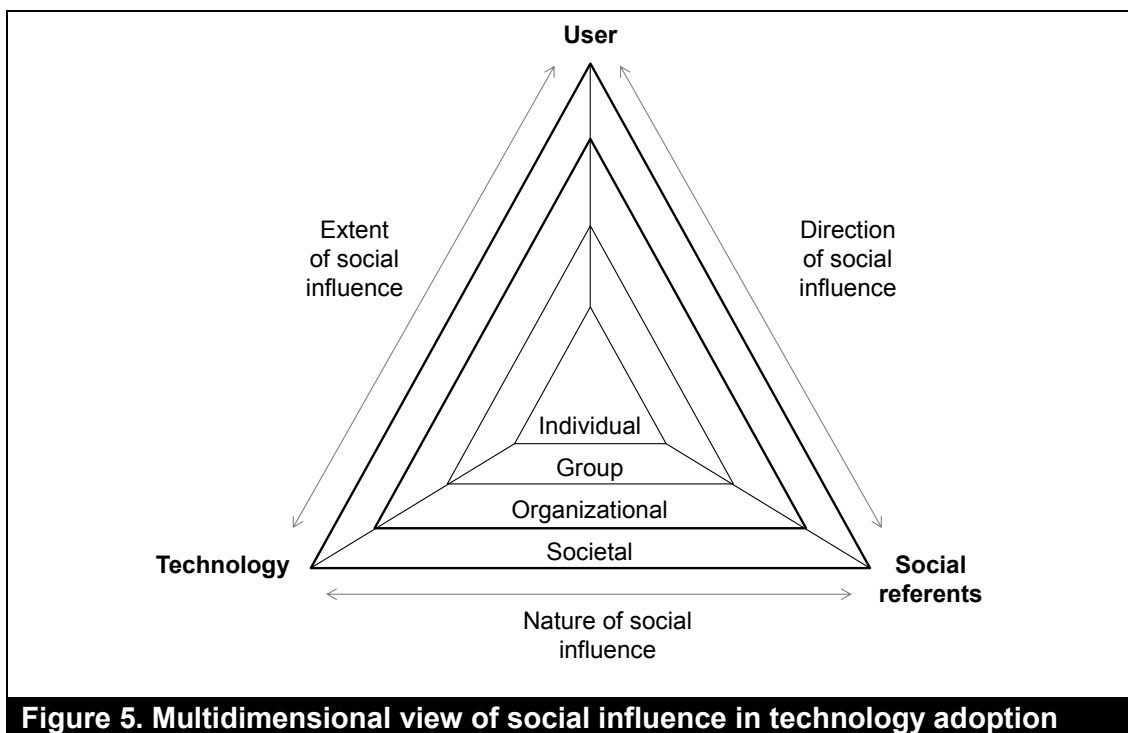


influence should be positioned within the nomological framework of technology adoption. Leading IS scholars have repeatedly identified limitations in the field's current conceptualizations of social influence and called for a better representation of social change processes (Bagozzi, 2007; Legris et al., 2003). Building upon the findings of this review, this review attempts to address some of these limitations by developing a framework to guide the further development of social influence research in IS.

Inspired by Leidner and Kayworth's (2006) tripartite definition of IT-culture conflict and Burton-Jones and Straub's (2006) conceptualization of system usage as a function of user-system-task, I propose a multidimensional view of social influence, as depicted in Figure 5. More specifically, I posit that social influence in technology adoption research should be viewed as the multi-level interaction of three dimensions: user, social referents, and technology. The interaction between the focal user and their social referents determines the direction of social influence, which may be reciprocal and multidirectional rather than just unidirectional. The interaction between user and technology, in turn, determines the extent of social influence as technology, which – as technology evolves from a tool level to a social level – should move beyond a one-to-one interaction between user and technology. Finally, the interaction between technology and social referents influences the nature of social influence – whether it is supportive or dismissive. In this regard, a more comprehensive representation of social referents' actual beliefs and behaviors toward a technology should be considered to improve the validity and explanatory power of this dimension. These interactions can take place at various structural levels of analysis, from individual to societal. The following paragraphs describe each proposed interaction in more detail.

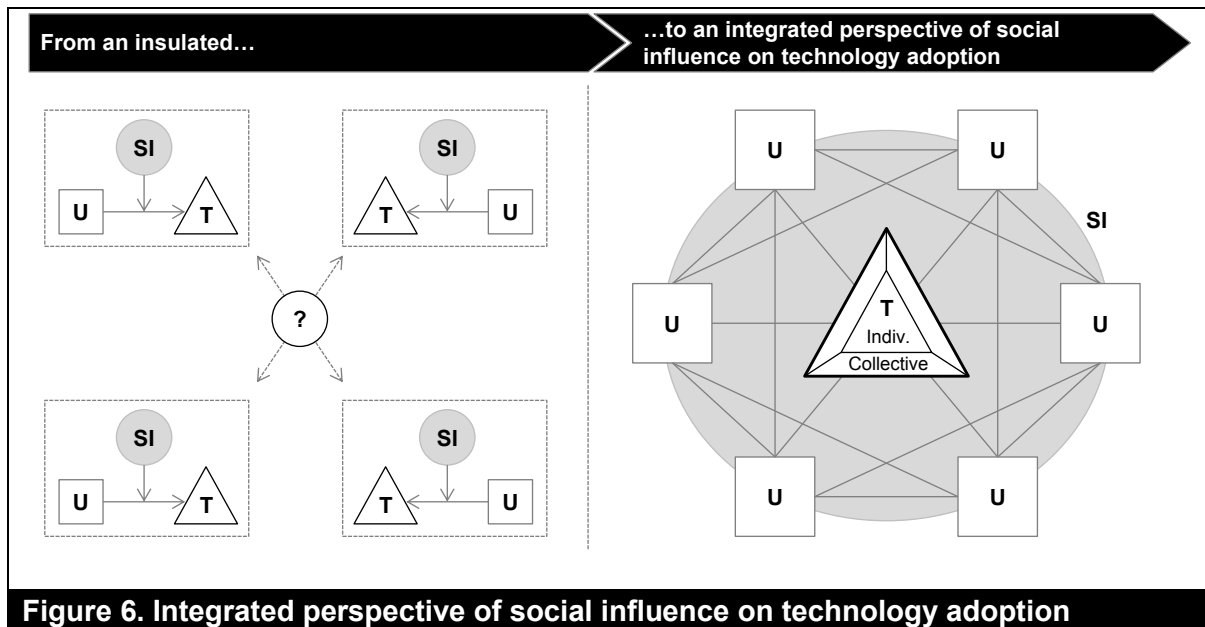
For one, IS scholars need to consider the interaction between (potential) users and their social referents. The majority of current social influence conceptualizations are predicated on a largely unidirectional view that see the individual as the target of social behavior, and not as the initiator of social interactions toward others (Bagozzi, 2007; Junglas et al., 2013). Norm-based definitions typically portray an individual at the receiving end of expectations put forth by others and posit a relationship characterized by dependence (Cialdini & Trost, 1998). While they do not presume that individuals necessarily comply or accept the expectations placed upon them, these definitions also remain mute on how the individual himself may affect and influence the social sphere that he is part of. Social behavior, however, is inherently reciprocal and based on multidirectional (involving multiple targets and multiple sources of influence), rather than unidirectional, interactions among individuals or groups (Moscovici, Mugny, & van

Avermaet, 1985). In line with Mason, Conrey, and Smith (2007), I propose that models that seek to adequately contextualize social influence processes with regard to technology adoption and use should incorporate reciprocal and multidirectional influence pathways. Network-based conceptualizations (e.g. social network configuration) provide a good basis, since they account for multiple actors and multidirectional influence pathways. However, they generally center on aggregate outcomes such as innovation diffusion rather than the social psychological processes driving behavioral intention. As such, a promising research avenue for IS scholars may be to study the social cognitive processes at the individual level through which multidirectional network effects drive technology adoption and use. At the group level, in turn, a better understanding is needed of how group interactions and dynamics influence individual and collective intentions to adopt or use a technology. Extensive conceptual and empirical research on these topics exists by social psychologists and IS scholars would do well to leverage it (see Mason et al., 2007 for a review).



For another, future IS research should consider the extent of interaction between users and technology, and what this implies for the sphere of influence in which social dynamics play a role. A number of scholars have criticized current technology adoption and usage models for being limited to a “one-to-one interaction between a user and an information system” (Junglas et al., 2013, p. 589). The user is typically seen as a “solitary information processor” (Sproull &

Faraj, 1997, p. 38) whose interaction with the system is restricted to the “tool level” – the technology (Wand & Weber, 1995). This reductionist perspective neglects the social component of IS technologies – the social interactions embedded within the use of a technology – and, in turn, limits our understanding of the social dynamics at play. For instance, an individual considering if and how to use a social technology such as Facebook will not only be influenced by social impulses prior to or post-use, but also by social impulses experienced while using the technology. The same applies to a group using a collaborative technology. The social influence processes at play may be similar to the ones already discussed, such as identification and internalization, but may include additional factors such as community feedback (Wattal et al., 2010), social interaction (Lee, 2009), and sociability (Junglas et al., 2013), which result from the user’s interaction with others members using the technology. As technology use becomes increasingly social, the extent to which it is subject to social influence will expand and evolve. This provides an exciting avenue for further research to deepen our understanding of how social components of technology use affect continued use.



\* U = user, T = technology, SI = social influence

Finally, the relationship between social referents and the salient technology needs to be considered. The nature of this interaction is likely to determine whether the social influence to use a technology is, for example, supportive or dismissive. In extant research, the nature of social influence is typically measured as function of others’ opinions as perceived by the focal individual, or through the manifestation of social referents’ use of the technology (e.g. critical mass). This leaves room and a need for more comprehensive representations of social referents’

actual beliefs and behaviors toward a technology. A number of studies have started to address this issue and, for instance, incorporated measures of co-workers' IT self-efficacy, perceived usefulness, and experience (Brown et al., 2010; Gallivan et al., 2005). In doing so, they aim to capture social referents' salient beliefs toward a technology more fully and objectively. At a collective level, the construct of group norm has been proposed to engender the group's shared beliefs toward a technology (Bagozzi & Lee, 2002). Future IS scholars should build on these ideas and consider how they can be developed further to better account for variations and nuances in social referents' beliefs. Or, more specifically, how does the social influence from a social referent who views the technology as useful but unwieldy, for instance, differ to that of a social referent who views it as accessible but not that useful – if at all?

Combining all these dimensions allows us to move from an insulated to an integrated perspective of social influence on technology adoption (Figure 6). Rich conceptualizations will view technology adoption and use not as a one-to-one interaction between a user and a system but as an interaction between a user and other users, *mediated* through technology – and set within a social sphere. Social influence research in IS already benefits immensely from its position at the interface of multiple research fields. Future scholars seeking to substantively advance our understanding will benefit from leveraging this pluralistic, interdisciplinary foundation and actively pursuing a richer, more holistic conceptualization of social influence that accounts for the interactions between user, social referents and technology in an integrated manner.

## **6. Recommendations and limitations**

If there is one dominant insight that has emerged from this review, it is that social influence is a highly complex concept with ample potential for future research within the technology adoption and use domain, as well as beyond. Throughout the paper, recommendations for future research have been made. Table 4 summarizes the most promising of these by clustering them into five main categories. These categories follow the sequence of the chapters in this paper, where the reader can find more detailed elaborations on each. I hope that these recommendations and examples will serve future IS scholars in further developing and enriching research on social influence with regard to technology adoption.

<b>Table 4. Summary of recommendations for technology adoption research</b>		
<b>Recommendation</b>	<b>Examples</b>	<b>Ref.</b>
1. Pursue an integrated, multi-theoretical understanding of social influence	<ul style="list-style-type: none"> <li>• Incorporate non-compliance-based social influence processes and conceptualizations</li> <li>• Acknowledge and leverage multi-theoretical foundation of social influence research</li> <li>• Further develop and validate measures of internalization and identification, e.g. group norms/social identity, in different contexts</li> <li>• Test how different social influence conceptualizations interact</li> <li>• Account for interactions between user, social referents, and technology (multi-directional social influence, social components of technology use, variance in social referents' beliefs/behaviors)</li> </ul>	4.1; 5
2. Move beyond the individual and explore other levels of analysis	<ul style="list-style-type: none"> <li>• Expand in particular on group-level research, for instance by leveraging process theory to study to how group dynamics and interactions manifest themselves as social influence and affect group attitudes toward technology adoption</li> <li>• Consider multiple levels of analysis, particularly when studying social or collaborative technologies in order to achieve more proximate representations of social influence</li> </ul>	4.2.1
3. Validate contingency effects	<ul style="list-style-type: none"> <li>• Explore contingency effects that remain inconclusive in extant research, e.g. work/non-work settings, as well as non-demographic/ non-environmental factors, e.g. technology anxiety</li> <li>• Test variance in contingency effects for different social influence processes</li> <li>• Test moderating impact of focal technology, i.e. social/non-social</li> </ul>	4.2.2; 4.2.3
4. Justify their use of construct measurements	<ul style="list-style-type: none"> <li>• Avoid lumping together conceptually and theoretically distinct social influence constructs – test the subordinate constructs separately in order to properly establish interrelation</li> <li>• Bypass common method bias from survey-based, self-reported data by capturing social referents' actual beliefs/ behaviors directly – where meaningful</li> <li>• Specify social referents when operationalizing social influence to account for variance among referents</li> </ul>	4.3.1; 4.3.2
5. Employ more diverse samples and longitudinal studies	<ul style="list-style-type: none"> <li>• Utilize more non-US and non-Chinese sample populations</li> <li>• Greater focus on technologically emergent markets such as Africa, Middle East, Africa and Asia (excl. China)</li> <li>• Conduct more longitudinal studies to investigate the sustained effects of social influence over time or with regard to continued use</li> </ul>	4.3.3; 4.3.4

The present paper is subject to a number of limitations that provide opportunities for future research. Specifically, there are four limitations that warrant further research: 1) limitations of the search approach, 2) non-inclusion of conference proceedings, 3) lack of statistical analysis, and 4) interdisciplinary nature of social influence construct.

First, there may be a certain bias in the sampled literature driven by the chosen keyword search methodology. While this is a methodologically sound approach for a topic-based literature search, it may skew construct-based searches, such as the present one, in favor of studies that

find positive evidence of the focal construct and, as a result, highlight it in the paper title, abstract or keywords (Webster & Watson, 2002). While not verifiable, the large number of studies in the sample with significant social influence constructs serve as an indication that this may be the case. However, since the primary aim of this literature review was to examine the range of social influence conceptualizations that exist in technology adoption research, this bias poses only a minor issue which was consciously accepted. The alternative – a restriction to one theoretical model and, consequently, one social influence concept (e.g. UTAUT) – would not have allowed this paper to capture the theoretical and conceptual spread that exists and that is characteristic of this research field. Scholars may account for a potential keyword bias by undertaking a full-text keyword search. However, since this is likely to result in a very large preliminary sample, additional boundary conditions may need to be applied.

Second, this review has not incorporated studies from conference proceedings. The reasoning behind this was driven by considerations of relevance and scope. For one, research on social influence in technology adoption is relatively mature, with few theoretically groundbreaking advances made in the recent past that are only likely to be found in conference proceedings. For another, the dominance of TAM/UTAUT-based journal articles (and associated uniformity of the social influence construct) in this research domain already posed a significant challenge in terms of scope, given the underlying aim of studying variance. This issue would have been exacerbated by also including conference proceedings. Nevertheless, in the interest of completeness, future IS research may benefit from incorporating conference proceedings in their reviews.

Third, this review engages in a conceptual comparison of different social influence constructs and draws on descriptive empirical data for support, but refrains from statistical analysis. In light of the variance in statistical support found for social influence across technology adoption studies, the research field may profit greatly from a meta-analysis of multiple social influence constructs. A meta-analysis may contribute to clarifying extant ambiguities in cause-effect relationships and provide a more meaningful comparison of effect sizes across different constructs. Scholars attempting to undertake such a meta-analysis should be aware of the methodological challenges entailed, in particular in terms of ensuring distinct constructs are defined and measured homogeneously within study settings that are identical or very similar in order for reliable comparisons and conclusions to be drawn.

Last, the interdisciplinary foundation of social influence research poses a challenge, both in terms of reviewing the concept in its full, interdisciplinary extent, and in developing guidelines for future research. The present paper focused on the technology adoption domain for its scoping of the salient literature and, where possible, tried to incorporate impulses from adjoining research domains in developing guidelines for future research. IS scholars should expand on this and seek a more active and in-depth exchange with associated research domains, such as social psychology and economics. Future reviews on social influence, in particular, may benefit from undertaking a selective review and comparison of literature from two or more research domains, rather than an in-depth, systematic review within one domain, in order to more effectively develop interdisciplinary insights.

## **7. Conclusion**

This paper set forth to review the literature on social influence in technology adoption research with the aim of informing scholars' understanding of the construct, its myriad conceptualizations, and its relevance to technology adoption research. This review has laid bare the ways in which social influence has been studied with regard to technology adoption in the last years and found indications of an increasing pluralism and interdisciplinary approach. Scholars interested in this field are encouraged to pursue an integrated, multi-theoretical understanding of social influence that accounts for the distinct theoretical mechanisms by which different social influence processes can affect technology adoption and positions social influence at the interface of user, technology, and social referents. As technology adoption becomes increasingly consumer-driven and social, the nature of social influence driving technology adoption will continue to evolve and provide a rich foundation for further research.

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## Appendix

### Appendix A: Additional tables

<b>Table A1. Classification of social and non-social technologies</b>	
Social technology	Non-social technology
Collaborative software (e.g. customer co-design websites) Blogs Email Groupware (e.g. Lotus Notes) Instant messaging (IM) Mobile services (text message, communications) Participation in virtual communities (e.g. public chat rooms, corporate knowledge communities, open source software communities) Social gaming Social media (e.g. Facebook, Twitter) Social shopping websites and group buying	3G technology Anti-spy software Internet (any purpose) Computer use (any purpose) E-commerce E-government technology E-health technology E-learning systems E-payment systems Electronic trading systems Enterprise software (e.g. CRM software, content management systems, procurement software, ERP system, knowledge management software) E-reader Internet/ mobile banking Mobile apps Mobile infotainment services Online games Self-service technology Word-processing

**Table A2. Measurement items of social influence constructs**

Construct	References	Scale	Typical measurement items
Subjective norm	Fishbein and Ajzen (1975)	SN1	People who influence my behavior think that I should use the system
		SN2	People who are important to me think that I should use the system
Social identity	Bagozzi and Lee (2002)	SI1	How would you express the degree of overlap between your own personal identity and the identity of the group you collaborate with through instant messaging?
		SI2	Please indicate to what degree your self-image overlaps with the identity of the group of partners as you perceive it
		SI3	How attached are you to the group you collaborate with through instant messaging?
		SI4	How strong would you say your feelings of belongingness are toward the group?
		SI5	I am a valuable member of the group
		SI6	I am an important member of the group
Image	Venkatesh and Davis (2000)	IM1	People who use the technology have a high profile
		IM2	People who use the technology have more prestige than those who do not
		IM3	Using the technology is a status symbol
Group norms	Bagozzi and Lee (2002)	Using instant messaging to communicate with the group of your friends that you identified above can be considered as a goal. For you and your friends, please estimate the strength to which each holds the goal:	
		GN1	Strength of the shared goal by yourself
		GN2	Average of the strength of the shared goal for other friends
Support	Thompson et al. (1991)	SP1	The senior management of this business has been helpful in the use of the system
		SP2	My supervisor is very supportive of the use of the system for my job
		SP3	In general, the organization has supported the use of the system
Social network configuration	Ibarra (1993)	Roster-based socio-metric approach (Wasserman & Faust, 1994) to determine:	
		Network composition	
		NC1	Homophily
		NC2	Range
		Relationship characteristics	
		RC1	Tie strength
		RC2	Density



<b>Construct</b>	<b>References</b>	<b>Scale</b>	<b>Typical measurement items</b>
Perceived critical mass	Lou et al. (2000)	PCM1	Most students in my class used instant messaging for team collaboration frequently
		PCM2	Most students in my group used instant messaging for team collaboration frequently
Social capital	Nahapiet and Ghoshal (1998) <sup>19</sup>	Structural dimension	
		SD1	Network ties
		SD2	Network configuration
		SD3	Appropriable organization
		Cognitive dimension	
		CD1	Shared codes and language
		CD2	Shared narratives
		Relational dimension	
		RD1	Trust
		RD2	Norms
		RD3	Obligations
		RD4	Identification

<sup>19</sup> Due to the conceptual nature of the paper, measurement items were not specified. Refer to Chiu et al. (2006) and Wasko and Faraj (2005).

Appendix B: Reviewed literature

Table B1. Construct, levels of analysis, focal technology, and moderating effects																					
Author	Social influence construct							Process			Level of analysis				Focal technology	Moderating effects					
	Subjective norm	Social capital	Social network	Social identity	Group norm	Critical mass	Support	Image	Compliance	Internalization	Identification	Individual	Group	Organization		Societal	Gender	Age	Experience	Culture	Voluntariness
Aboelmaged 2010	*							*			*					e-procurement					
Agarwal et al. 2009			*					*	*		*					Internet (general)					
Akar and Mardikyan 2014	*								*		*					social media					
Al-Gahtani 2004									*	*	*					PC use					
Al-Qeisi et al. 2015	*							*	*					*	Internet banking	*	*	*		*	
Bagozzi and Dholakia 2002	*			*	*			*	*	*	*	*			virtual communities						
Bagozzi and Dholakia 2006				*						*	*	*			OSS user communities			*			
Baron et al. 2006				*						*	*				text message						
Brown et al. 2010	*							*			*	*			1) sms use, 2) collaboration technology	*	*	*			
Bruque et al. 2009			*					*	*		*				ERP system						
Chan and Lu 2004	*						*	*	*	*	*				Internet banking						
Chan et al. 2010	*							*			*				e-gov technology						
Chatterjee et al. 2015	*							*	*		*				Internet (general)						
Chau and Hu 2001	*							*			*				telemedicine						
Chau and Hu 2002	*							*			*				telemedicine						
Chen et al. 2009	*							*	*		*				self-service technology						
Cheng 2011	*					*		*	*		*				e-learning system						
Cheung et al. 2000	*							*			*				Internet (general)						

Author	Social influence construct								Process			Level of analysis				Focal technology	Moderating effects					
	Subjective norm	Social capital	Social network	Social identity	Group norm	Critical mass	Support	Image	Compliance	Internalization	Identification	Individual	Group	Organization	Societal		Gender	Age	Experience	Culture	Voluntariness	Other
Chiu et al. 2006		*	*	*					*	*	*	*	*			virtual community						
Choi and Geistfeld 2004	*								*					*		online shopping			*			
Datta 2011	*			*	*				*	*	*			*		e-commerce						
Devaraj et al. 2008	*								*			*				collaboration technology						personality
Dholakia et al. 2004				*	*					*	*	*	*			virtual communities						
Dickinger et al. 2008	*									*		*				push to talk mobile tech						
Dinev and Hu 2007	*								*			*				anti-spyware						
Elie-Dit-Cosaque et al. 2012							*			*		*				work-related IT						
Faullant et al. 2012	*			*			*	*	*	*	*	*				mobile voting						
Foon and Fah 2011	*					*	*	*	*	*	*	*				Internet banking						
Fusilier and Durlabhji 2005	*								*			*				Internet (general)		*				attitude, PBC
Gallivan et al. 2005					*	*			*	*		*	*			IT use (general)						
Gao and Bai 2014	*								*			*				Internet of things						
Gounaris and Koritos 2008						*	*		*	*	*	*				Internet banking						
Gupta et al. 2008	*						*		*	*	*	*				e-gov ICT	*					
Guzzo et al. 2015			*						*	*		*				n/a						
Hong and Tam 2006	*								*	*		*				mobile infotainment services						
Hong et al. 2008	*								*			*				mobile data services						
Hsieh et al. 2008	*								*			*				Internet TV						
Hsieh et al. 2011	*	*					*		*	*	*	*				Internet (general)						

Author	Social influence construct								Process			Level of analysis				Focal technology	Moderating effects					
	Subjective norm	Social capital	Social network	Social identity	Group norm	Critical mass	Support	Image	Compliance	Internalization	Identification	Individual	Group	Organization	Societal		Gender	Age	Experience	Culture	Voluntariness	Other
Hsu and Lu 2004	*					*			*	*		*				online games						
Ilie et al. 2005						*			*	*		*				instant messaging	*					
Irani et al. 2009	*								*			*				Internet (general)						
Jaradat and Al Rababaa 2013	*								*			*				mobile commerce	*	*	*			
Johnston and Warkentin 2010	*						*		*	*		*				anti-spy software						
Junglas et al. 2013				*							*	*				second life						
Khalifa and Shen 2008	*								*	*		*				mobile commerce						
Kim et al. 2007	*					*			*	*		*				word-processing						
Kleijnen et al. 2004	*								*			*				wireless finance/m-commerce						
Kvasny and Keil 2006		*					*			*		*				Internet (general)						
Lau et al. 2001	*								*			*				online trading						
Lee et al. 2013	*	*	*	*					*	*	*			*		tourism technology						
Lewis et al. 2003	*									*		*				Internet use						
Li et al. 2005				*		*			*	*	*	*				instant messaging						
Li et al. 2008	*								*	*		*				national identity system						
Liang et al. 2010	*				*		*		*	*		*	*			computerized physician order entry system						
Liao and Chou 2012	*	*	*	*					*	*	*		*			virtual community						
Lou et al. 2000						*			*	*		*				groupware (Lotus Notes)						
Lu and Hsiao 2007	*								*	*		*				online blog use						

Author	Social influence construct								Process			Level of analysis				Focal technology	Moderating effects					
	Subjective norm	Social capital	Social network	Social identity	Group norm	Critical mass	Support	Image	Compliance	Internalization	Identification	Individual	Group	Organization	Societal		Gender	Age	Experience	Culture	Voluntariness	Other
Lu et al. 2003a	*						*	*		*	*					wireless Internet via mobile technology						
Lu et al. 2003b	*								*		*					wireless Internet via mobile technology						
Lu et al. 2005	*						*	*	*	*	*					wireless Internet via mobile technology						
Macredie and Mijinyawa, 2011	*							*						*		open source software						
Magni et al. 2013			*					*	*		*	*				CRM software						
Mardikyan et al. 2012	*							*			*					3G technology						
McCoy et al. 2005	*							*						*		email				*		
Ming-Chi 2009	*							*			*					online games	*	*	*	*		
Montazemi 2008			*					*	*		*					electronic trading systems						
Morris and Venkatesh 2000	*							*			*					enterprise SW for data retrieval		*	*			
Mutlu and Ergeneli 2012	*							*	*		*					email				*		
Neufeld et al. 2007	*							*			*					enterprise software						
Nysveen et al. 2005a	*						*	*		*	*					mobile chat services	*					
Nysveen et al. 2005b	*							*			*					mobile services						
Pavlou and Fygenson 2006	*							*			*					e-commerce						

Author	Social influence construct								Process			Level of analysis				Focal technology	Moderating effects					
	Subjective norm	Social capital	Social network	Social identity	Group norm	Critical mass	Support	Image	Compliance	Internalization	Identification	Individual	Group	Organization	Societal		Gender	Age	Experience	Culture	Voluntariness	Other
Peng et al. 2014			*					*	*					*		health information systems						
Plouffe et al. 2001						*	*	*	*	*		*				smart card-based payment system						
Rauniar et al. 2014						*		*	*		*					social media						
Riquelme and Rios 2010							*			*	*					mobile banking	*					
Sarker and Valacich 2010					*				*			*				flowchart software						
Sarker et al. 2005					*				*			*				organizational hard-/software						
Shen 2012				*						*	*					social shopping	*					
Shen et al. 2010	*			*	*			*	*	*	*	*	*			instant messaging						
Shen et al. 2013	*			*	*	*		*	*	*	*	*	*			instant messaging						
Sledgianowski and Kulviwat 2009	*					*		*	*		*					social network sites						
Son et al. 2012							*			*	*					Collaborative customer co-design websites						
Srite and Karahanna 2006	*							*			*					PC + PDA use			*			
Strader et al. 2007						*		*	*		*					instant messaging, email						
Sun et al. 2013	*							*			*					m-health services						
Sykes et al. 2009			*					*	*		*					content management system						
Thakur and Srivastava 2013	*						*	*	*	*	*					mobile commerce						
Titah and Barki 2009	*							*			*					organizational IT applications						
Tsai and Bagozzi 2014	*			*	*				*	*	*	*				virtual communities						

Author	Social influence construct								Process			Level of analysis				Focal technology	Moderating effects					
	Subjective norm	Social capital	Social network	Social identity	Group norm	Critical mass	Support	Image	Compliance	Internalization	Identification	Individual	Group	Organization	Societal		Gender	Age	Experience	Culture	Voluntariness	Other
Van Slyke et al. 2007	*					*			*	*		*				instant messaging						
Venkatesh and Brown 2001	*						*	*	*		*					PC adoption						
Venkatesh and Davis 2000	*						*	*	*	*	*					organizational IT applications			*		*	
Venkatesh and Morris 2000	*							*			*					organizational IT applications	*		*			
Venkatesh and Sykes 2013			*					*	*		*					Internet (general)						
Venkatesh and Zhang 2010	*					*		*	*					*		enterprise SW	*	*	*	*	*	
Venkatesh et al. 2000	*							*			*					enterprise SW	*		*			
Venkatesh et al. 2003	*					*		*	*		*					organizational IT	*	*	*		*	
Venkatesh et al. 2004	*							*			*					organizational IT	*					
Venkatesh et al. 2011			*					*	*		*					e-health system						
Wang and Chou 2014	*					*		*	*		*					online group buying						
Wang et al. 2013				*	*				*	*	*	*				knowledge management software						
Wasko and Faraj 2005		*	*	*			*	*	*	*	*					virtual community						
Wattal et al. 2010						*		*	*		*					corporate blogs	*	*				
White Baker et al. 2007	*							*						*		PC use	*	*				education
Williams et al. 2014	*						*	*	*	*	*					e-reader						
Wu and Chen 2005	*							*			*					online tax						
Ya-Ching 2006	*					*		*	*		*					e-learning system					*	
Yang 2013	*							*	*		*					mobile apps						
Yang and Forney 2013	*					*		*	*		*					mobile shopping						tech anxiety
Yang et al. 2012	*							*	*					*		mobile viral behavior			*			
Yu 2012	*					*		*	*		*					mobile banking	*	*				
Zhang et al. 2006	*										*					e-commerce						

Table B2. Social reference group, study setting, study design, and sample details																				
Author	Social reference group									Study setting				Design		Sample details				
	people	friends/peers	family/relatives	co-workers	superiors	subordinates	organization	government	media	voluntary	mandatory	work	non-work	cross-sectional	longitudinal	student	non-student	mixed	sample size	country
Aboelmaged 2010	*									*		*		*			*		316	UAE
Agarwal et al. 2009		*								*			*	*			*		45212	US
Akar and Mardikyan 2014	*									*			*	*				*	462	Turkey
Al-Gahtani 2004	*										*	*		*			*		1190	Saudi Arabia
Al-Qeisi et al. 2015	*						*			*			*	*				*	776	Jordan, Saudi Arabia, Egypt
Bagozzi and Dholakia 2002		*								*			*	*				*	157	US
Bagozzi and Dholakia 2006		*								*			*	*				*	402	23 countries
Baron et al. 2006		*	*							*			*	*	*				118	UK/US
Brown et al. 2010				*	*					*		*	*	*			*		796	Finland
Bruque et al. 2009	*										*	*		*			*		371	Spain
Chan and Lu 2004		*	*	*						*			*	*	*				499	China
Chan et al. 2010	*										*		*	*			*		1179	China
Chatterjee et al. 2015		*								*			*	*		*			n/a	US
Chau and Hu 2001	*									*		*		*			*		408	China
Chau and Hu 2002	*									*		*		*			*		400	China
Chen et al. 2009	*									*			*	*	*		*		481	Taiwan
Cheng 2011		*	*	*	*			*			*	*		*			*		328	Taiwan
Cheung et al. 2000				*	*					*		*		*		*			241	China
Chiu et al. 2006				*						*		*		*			*		310	Taiwan
Choi and Geistfeld 2004	*									*			*	*	*		*		755	US, Korea
Datta 2011				*						*			*	*			*		172	37 countries



Author	Social reference group									Study setting				Design		Sample details				
	people	friends/peers	family/relatives	co-workers	superiors	subordinates	organization	government	media	voluntary	mandatory	work	non-work	cross-sectional	longitudinal	student	non-student	mixed	sample size	country
Devaraj et al. 2008	*									*			*	*	*				180	n/a
Dholakia et al. 2004		*								*			*	*			*		545	US
Dickinger et al. 2008		*	*							*			*	*			*		245	Germany
Dinev and Hu 2007	*									*			*	*			*		332	US
Elie-Dit-Cosaque et al. 2012					*					*		*		*		*			724	France
Faullant et al. 2012	*	*								*			*	*			*		136	Germany
Foon and Fah 2011	*									*			*	*			*		200	Malaysia
Fusilier and Durlabhji 2005	*									*			*	*	*				269	India
Gallivan et al. 2005				*						*		*		*		*			96	US
Gao and Bai 2014	*									*			*	*			*		368	China
Gounaris and Koritos 2008	*									*			*	*			*		1943	Greece
Gupta et al. 2008	*				*		*			*		*		*		*			102	India
Guzzo et al. 2015	*																		n/a	n/a
Hong and Tam 2006	*									*			*	*			*		808	China
Hong et al. 2008	*									*			*	*			*		811	China
Hsieh et al. 2008		*	*					*		*		*	*	*		*			451	US
Hsieh et al. 2011		*	*							*		*	*	*		*			784	US
Hsu and Lu 2004		*								*		*	*	*			*		233	Taiwan
Ilie et al. 2005	*									*		*	*	*	*				279	US
Irani et al. 2009		*	*	*						*		*	*	*			*		358	UK
Jaradat and Al Rababaa 2013	*									*		*	*	*	*				447	Jordan
Johnston and Warkentin 2010		*								*		*	*	*			*		311	US
Junglas et al. 2013	*									*		*	*	*	*				263	US
Khalifa and Shen 2008	*									*		*	*	*			*		202	China
Kim et al. 2007				*	*	*				*	*	*	*	*		*			262	Korea

Author	Social reference group									Study setting				Design		Sample details				
	people	friends/peers	family/relatives	co-workers	superiors	subordinates	organization	government	media	voluntary	mandatory	work	non-work	cross-sectional	longitudinal	student	non-student	mixed	sample size	country
Kleijnen et al. 2004		*	*							*			*	*			*	105	Netherlands	
Kvasny and Keil 2006		*	*							*			*		*		*	90	US	
Lau et al. 2001	*									*			*	*		*		178	China	
Lee et al. 2013	*	*		*						*	*			*		*		303	US	
Lewis et al. 2003				*	*					*	*			*		*		226	US	
Li et al. 2005		*								*			*	*	*			273	US	
Li et al. 2008	*									*			*	*	*			443	US	
Liang et al. 2010				*						*	*			*		*		103	China	
Liao and Chou 2012		*		*						*			*	*			*	318	China	
Lou et al. 2000		*								*			*	*	*			385	US	
Lu and Hsiao 2007		*								*			*	*			*	525	Taiwan	
Lu et al. 2003a	*									*			*	*	*			128	China	
Lu et al. 2003b	*																	n/a	n/a	
Lu et al. 2005	*	*								*			*	*	*	*		357	US	
Macredie and Mijinyawa, 2011				*				*		*	*		*	*		*		10	UK	
Magni et al. 2013				*						*	*		*	*		*		265	US	
Mardikyan et al. 2012	*									*			*	*			*	150	Turkey	
McCoy et al. 2005	*									*			*	*	*	*		263	Uruguay, US	
Ming-Chi 2009	*		*							*			*	*			*	628	Taiwan	
Montazemi 2008	*									*	*		*	*		*		90	Canada	
Morris and Venkatesh 2000	*									*	*		*	*	*	*		118	US	
Mutlu and Ergeneli 2012	*									*	*		*	*		*		286	Turkey	
Neufeld et al. 2007	*	*		*						*	*		*	*		*		209	Canada	
Nysveen et al. 2005a	*									*			*	*			*	684	Norway	
Nysveen et al. 2005b	*									*			*	*	*	*		2038	Norway	

Author	Social reference group									Study setting				Design		Sample details				
	people	friends/peers	family/relatives	co-workers	superiors	subordinates	organization	government	media	voluntary	mandatory	work	non-work	cross-sectional	longitudinal	student	non-student	mixed	sample size	country
Pavlou and Fygenson 2006	*									*			*		*			*	312	US
Peng et al. 2014							*			*	*				*		*		38506	US
Plouffe et al. 2001	*			*						*	*				*			*	604	Canada
Rauniar et al. 2014		*		*						*		*		*				*	389	US
Riquelme and Rios 2010				*						*		*		*				*	681	Singapore
Sarker and Valacich 2010				*	*					*		*		*		*			297	US
Sarker et al. 2005				*						*	*								n/a	n/a
Shen 2012		*								*		*		*		*			230	US
Shen et al. 2010	*									*		*		*		*			482	China
Shen et al. 2013	*	*								*		*		*		*			227	China
Sledgianowski and Kulviwat 2009	*									*		*		*		*			289	US
Son et al. 2012	*									*		*		*		*			223	US
Srite and Karahanna 2006		*	*		*					*		*		*		*			297	30 countries
Strader et al. 2007	*	*	*							*		*		*		*			163	US
Sun et al. 2013	*									*		*		*			*		204	China
Sykes et al. 2009				*						*	*			*			*		87	Finland
Thakur and Srivastava 2013	*						*			*		*		*				*	292	India
Titah and Barki 2009	*									*	*			*			*		258	n/a
Tsai and Bagozzi 2014	*	*								*		*		*				*	972	Taiwan
Van Slyke et al. 2007	*	*								*		*		*		*			270	US
Venkatesh and Brown 2001		*	*					*		*		*		*				*	733	US
Venkatesh and Davis 2000	*									*	*	*		*			*		156	US
Venkatesh and Morris 2000	*										*	*		*			*		342	US
Venkatesh and Sykes 2013		*								*		*		*			*		210	India

Author	Social reference group									Study setting				Design		Sample details				
	people	friends/peers	family/relatives	co-workers	superiors	subordinates	organization	government	media	voluntary	mandatory	work	non-work	cross-sectional	longitudinal	student	non-student	mixed	sample size	country
Venkatesh and Zhang 2010	*				*		*				*	*			*		*		350	US, China
Venkatesh et al. 2000	*									*		*			*		*		355	US
Venkatesh et al. 2003	*										*	*		*			*		348	US
Venkatesh et al. 2004	*									*		*			*		*		552	US
Venkatesh et al. 2011				*							*	*			*		*		1120	US
Wang and Chou 2014	*									*			*	*				*	1163	Taiwan
Wang et al. 2013				*	*	*				*		*			*		*		83216	54 countries
Wasko and Faraj 2005				*						*		*		*		*			173	US
Wattal et al. 2010				*	*					*		*		*		*			2291	US
White Baker et al. 2007	*									*		*		*		*			1088	Saudi-Arabia
Williams et al. 2014	*									*		*		*			*		234	UK
Wu and Chen 2005	*									*		*		*		*			1032	Taiwan
Ya-Ching 2006		*			*					*	*		*	*	*	*			1085	Taiwan
Yang 2013	*									*		*		*	*	*			555	US
Yang and Forney 2013	*	*								*		*		*				*	400	US
Yang et al. 2012	*									*		*		*	*	*			835	Us, China
Yu 2012	*									*		*		*			*		441	Taiwan
Zhang et al. 2006	*									*		*		*	*	*			294	US

# **Mechanisms of engagement with, and disengagement from, Internet applications: A qualitative study of online job search**

*Annika Reinartz, Katharina Buhtz*

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## **Abstract**

In the context of increasing digitization and persistent digital inequality, scholars have sought to uncover the mechanisms that explain why people engage with, or disengage from, Internet applications. We provide a new vantage to this societally relevant conversation by conducting a qualitative study among 16 job-seekers in Germany who differ substantially in how they use online job search applications. Adopting coping theory as the theoretical foundation of our emerging understanding, we develop a dynamic perspective of how an individual's resources – social capital, cultural capital, and habitus – as well as further contextual factors – perceived risk and trust in social capital – determine the appraisal of and the decision to use Internet applications or to abandon them. Our findings highlight the value of adopting a process-based view in order to gain a more thorough understanding of the mechanisms that lead to (dis-)engagement. In particular, our model suggests that social capital plays a more important role in engaging people with Internet applications than portrayed in previous studies. Our research carries important implications for information systems scholars and for policy makers seeking to bridge digital divides.

**Keywords:** Online job search, digital labor market, coping theory, capital theory, digital inequality, ICT adoption, ICT avoidance, ICT resistance, ICT use

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## **1. Introduction**

Exploring what drives individual responses to new technologies has long been at the heart of information systems research. As more and more aspects of people's lives shift online, understanding what drives individuals to use – or, more importantly still, *not* to use – digital technologies is now more relevant than ever. In fact, scholars have voiced concerns that taking part in digitization is becoming a prerequisite to fully participate in society (Hargittai, 2003) and identified “digital inequality” (DiMaggio et al., 2004) as one of the main challenges of the digitizing society. Digital inequality denotes the phenomenon that social inequalities may be amplified, rather than mitigated, through digitization because certain individuals profit less from digital opportunities due to limited access and limited abilities to *use* information and communication technologies (ICT). Scholars have emphasized that the persistence of digital inequality is problematic because Internet applications permeate almost all domains of life by enhancing or, increasingly, even substituting offline services in areas as fundamental to life chances as education, employment and health (Chen, Lee, Straubhaar, & Spence, 2014; Lindsay, 2005; Riggins & Dewan, 2005; Wei et al., 2011). As such, it is imperative to understand why and how individuals respond to Internet applications (Hsieh et al., 2011; Kvasny & Keil, 2006).

In this vein, information systems scholars have developed a wide range of models to explain human behavior towards technologies. One principal stream of research has leveraged a variance-based perspective to explore the antecedents of technology use and adoption, such as an individual's beliefs about how useful a technology is and how easy it is to use that technology (Venkatesh et al., 2003). Some of the best known and most commonly used technology adoption models have emerged from this variance-based research perspective, such as the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003, 2012). In contrast, another principal, albeit smaller, stream of research has adopted a process-based perspective to explore the mechanisms and causal processes that determine technology use and adaptation behavior (Maxwell, 2004; Orlikowski, 1996). Process-based approaches offer the opportunity to study user behavior towards a technology as a dynamic and ongoing decision process and thereby account for the rich and complex nature of behavioral responses (Schultze & Orlikowski, 2004).

Coping theory represents one of the most popular theoretical lenses through which to study user behavior from a process-based perspective. Coping theory is rooted in psychology and

posits that individuals deal with arising internal and external demands, such as being faced with a new technology, through a two-step cognitive process of appraisal and coping effort (Lazarus & Folkman, 1984; Lazarus, 1966). Ultimately, this process decides whether and how individuals choose to engage with, or disengage<sup>20</sup> from, the technology. Information systems (IS) research has incorporated coping theory as a useful lens to explore user adaptation to new technologies. For example, Ortiz de Guinea and Webster (2013) found that individuals appraise expected and unexpected IT difficulties differently and cope through distinct emotional, cognitive and behavioral reactions, some of which occur as part of an automatic and others as part of an adaptive response.

While coping theory acknowledges the vital role of individual resources on the coping process, it remains relatively mute regarding the exact nature of these resources, particularly in the context of new technologies (Beaudry & Pinsonneault, 2005; Lazarus & Folkman, 1984). More specifically, it remains unclear which individual resources play a role at each stage of the coping process and how these resources interact with one another. To this end, capital theory can provide a theoretical vantage point from which to explore these questions. Rooted in sociology, capital theory posits that human behavior is explicable through people's access to, or lack of, resources such as knowledge and skills, social support, and economic means (Becker, 1975; Bourdieu, 1984; Coleman, 1990). Within IS research, scholars have successfully adopted capital theory to explain individual differences in Internet use (Kvasny & Keil, 2006; Lam & Lee, 2006). Hsieh and colleagues (2011), for example, found that socio-economically disadvantaged individuals differ from more advantaged individuals in their use of Internet TV because, among other factors, they have less access to cultural capital.

This paper aims to deepen our current understanding of user behavior towards new technologies by adopting a coping theoretical lens to dissect the cognitive processes leading to (dis-)engagement and exploring the capital resources that influence this process. Coping theory is particularly suited to study technology adoption because it allows us to explore the cognitive processes and actions that occur prior to, during and after using a new technology. This perspective on user (dis-)engagement as the result of an iterative coping process provides a unique vantage point from which to capture the dynamic nature of user responses. Moreover, we hope to further enrich this perspective by drawing on capital theory to relate how resources affect different stages of the coping process. We propose that adopting a coping perspective

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<sup>20</sup> In the remainder of this paper, we summarize "engagement or disengagement" with "(dis-)engagement"

and accounting for the relational impact of capital resources on the coping process can deepen our understanding of which mechanisms lead individuals to engage with, or disengage from, technologies.

To explore individual user behavior towards digital technologies we conducted a qualitative, inductive study of individuals' (dis-)engagement with Internet applications in the context of online job search. Based on 16 in-depth, semi-structured interviews with job-seekers from two regions in Germany we develop a coping model of user (dis-)engagement and relate how individual capital resources influence different stages of the coping process. The model allows us to better understand how coping mechanisms and capital resources interact to jointly determine whether an individual successfully engages with an Internet application or drops out at some point along the way. Most importantly, our emerging theory suggests that social capital has a game-changing impact at all stages of the coping process and can make the difference between engagement and disengagement.

Our study primarily contributes to the ongoing information systems research debate on a richer understanding of technology use and adoption (Burton-Jones & Grange, 2012; Hsieh et al., 2011; Venkatesh et al., 2007). In contrast to existing research, our model explicitly incorporates the dynamic nature of use while capturing the individual and contextual factors influencing it. Further, we challenge extant notions on the importance of different capital resources in information systems research by highlighting the game-changing role of social capital and introducing a more differentiated perspective on Internet skills. In addition, our study also contributes to digital inequality research by identifying the factors that lead to critical outcomes such as involuntary digital exclusion (Hargittai & Hinnant, 2008; Kvasny & Keil, 2006). Finally, our research has important implications for public policy by uncovering promising points for intervention.

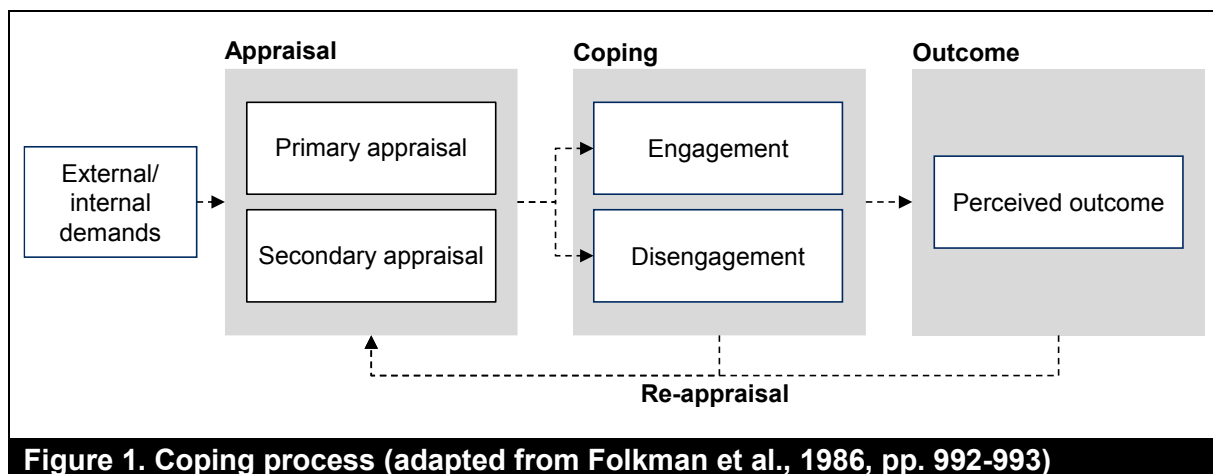
## **2. Theoretical foundation**

### **2.1 Coping theory and engagement with new technologies**

Psychologists developed the cognitive-phenomenological theory of stress and coping (Coyne & Lazarus, 1980; Lazarus & Folkman, 1984; Lazarus, 1966) to explain how and why individuals vary in their adaptation efforts when responding to a given change in their environment. Lazarus and Folkman (1984, p. 141) define coping as “the cognitive and behavioral efforts exerted to manage specific external and/or internal demands that are



appraised as taxing or exceeding the resources of the person.” Cognitive efforts comprise mental attempts of adaptation such as accepting or distancing oneself from an internal or external demand with the goal of changing the perceived significance of the situation; behavioral efforts comprise actions such as learning new skills or talking to others with the goal of changing the situation itself (Folkman & Lazarus, 1985; Lazarus & Folkman, 1984). External demands refer to demands originating from the socio-contextual environment of an individual while internal demands refer to those emanating from the individual itself, for instance, an individual’s aim to get promoted quickly (Lazarus & Folkman, 1984). Coping theory considers the interaction between the individual and the situation as a dynamic process, which can evolve and change as a result of developments in the individual’s behavior and the situation (Carver & Scheier, 1994).



**Figure 1. Coping process (adapted from Folkman et al., 1986, pp. 992-993)**

Coping theory identifies two sub-processes of the coping process, namely the cognitive appraisal of a situation and the coping effort itself, and considers the immediate outcomes of the process as well as a potential re-appraisal of the situation (Folkman, Lazarus, Dunkel-Schetter, DeLongis, & Gruen, 1986; Lazarus, 1966). The coping process is illustrated in Figure 1. The cognitive appraisal process comprises the primary and the secondary appraisal. During primary appraisal individuals assess if a change in the environment is of personal relevance to them and how they would be affected (Lazarus & Folkman, 1984; Lazarus, 1966). Coping theory suggests that an individual can appraise a specific event in three distinct ways: (1) as irrelevant, if the person perceives the event as not having any implications for the own well-being; (2) as a potential threat, if the individual fears to be harmed; or (3) as an opportunity, if the individual construes the event as potentially positive. Information systems research often categorizes changes in the environment either as an opportunity for the individual (Beaudry & Pinsonneault, 2005) – which implies perceived, potentially positive consequences, or as a threat

– which implies perceived, potentially negative consequences (Carpenter, 1992). However, changes in the environment can be multi-faceted and comprise aspects of all possible primary appraisal outcomes, not just one (Lazarus & Folkman, 1984). During secondary appraisal individuals assess what can be done to cope with the situation given the individual resources available (Lazarus & Folkman, 1984). In other words, individuals evaluate their social, cognitive, psychological, physical, and financial resources and determine the level of control they feel to have in the situation. It is important to note that these resources “refer not to what people do, but to what is available to them in developing their coping repertoires” (Pearlin & Schooler, 1978, p. 5). Consequently, the perceived level of control given the resources at hand influences and mobilizes the coping efforts employed by the individual (Lazarus & Folkman, 1984).

Following the cognitive appraisal, individuals engage in coping efforts, i.e. take actions to deal with the change in their environment. While a vast range of specific coping strategies have been studied by psychologists (Scherer, 1999), coping efforts are often categorized as engagement and disengagement strategies<sup>21</sup> (Skinner, Edge, Altman, & Sherwood, 2003). Fundamental to this categorization of coping efforts is “the contrast between ways of coping that bring the individual into closer contact with the stressful situation as opposed to ways of coping that allow the individual to withdraw” (Skinner et al., 2003). Accordingly, engagement strategies refer to actions taken by an individual that aim at reducing the person-environment tension by changing the situation itself. For example, a user might seek support in order to learn how to effectively use a new Internet application. In contrast, disengagement strategies comprise actions taken by an individual that aim at regulating emotional distress by changing one’s perception of the situation without changing the situation itself (Gutiérrez, Peri, Torres, Caseras, & Valdés, 2007). For example, a user might convince herself that a certain Internet application is not relevant for her. Depending on the cognitive appraisal of the situation, coping efforts can range from escaping the situation – e.g., by strategic ignorance (Merton, 1987) or

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<sup>21</sup> In psychology, an alternative and widely used categorization is problem-focused and emotion-focused coping. For example, Beaudry and Pinsonneault (Beaudry & Pinsonneault, 2005) built on the distinction between problem-focused and emotion-focused coping to develop the coping model of user adaptation which comprises four coping strategies that contain elements of both problem-focused and emotion-focused acts. In line with Ortiz de Guinea and Webster (2013), we deliberately rather focus on a distinction between engagement and disengagement, given that these categories are exclusive (Carver & Connor-Smith, 2010) as opposed to being interrelated and complementary (Folkman & Lazarus, 1980, 1985). Additionally, Carver and Connor-Smith (2010) found the distinction between engagement and disengagement to be of highest importance in practice.

by quitting a job (Begley, 1998) – to making an effort to leverage the situation – e.g., by seeking support in order to embrace new routines (Carver & Connor-Smith, 2010).

The coping process as a whole is iterative, meaning that a continual re-appraisal of the situation takes place based on the evolving interaction between the internal and external demands on the individual and the individual's resources. As such, the coping process is characterized by its dynamic and resource-dependent nature (Lazarus, 1966). Changes in the socio-contextual environment of the individual or in the personal, subjective relevance of the event can lead to a new appraisal of an event (Folkman & Lazarus, 1985). Furthermore, the chosen coping effort and the following experienced outcomes can result in a re-appraisal of the event (Beaudry & Pinsonneault, 2005). For instance, if an individual appraises a new technology at work as an opportunity to increase her performance, actively engages in learning the new skills required to operate the technology, but then perceives the outcomes of her efforts to be negative – e.g. because the skills are too complex to acquire or the subjective performance does not increase – she may change her prior appraisal and may no longer view the new technology as an opportunity.

Coping theory has proven to be an insightful lens in information systems research. More specifically, IS researchers have applied coping theory to better understand why and how individuals react to new technologies. For example, Lee and Larsen (2009) build on coping theory to study executives' decision to adopt anti-malware software. Similarly, Liang and Xue (2009) draw on coping theory to develop a dynamic perspective on how individuals behave to avoid malicious information technologies. Furthermore, in their Coping Model of User Adaptation (CMUA), Beaudry and Pinsonneault (2005) show that exploring the distinct stages of the coping process can be helpful in better understanding the cognitive processes individuals go through and the actions individuals take when deciding how to adapt to a new technology in an organizational context. The dynamic perspective of coping theory makes it particularly suitable to study complex individual use patterns that span over a period of time, such as (dis-)engagement with a new technology. Coping theory has also proven to be an insightful lens to explain individual behavior in both mandatory and quasi-mandatory settings, where individuals are not forced but expected to make use of a new technology (Beaudry & Pinsonneault, 2010), as is the case with many Internet applications today as they increasingly substitute offline alternatives.

## **2.2 The influence of capital resources on engagement with new technologies**

Coping theory suggests that individual resources play an important role in how individuals appraise and cope with a novel situation (Lazarus and Folkman 1984), such as being faced with a new technology. Yet, it remains relatively mute regarding the exact nature of these resources, particularly in the context of new technologies. Here, IS literature can provide meaningful insights regarding which individual resources typically influence the adoption and use of a new technology. More specifically, IS scholars seeking to adopt a resource-based view to explain individual behavior towards new technologies have built on capital theory (Hsieh et al., 2011; Lam & Lee, 2006; Lindsay, 2005).

Capital theory is rooted in sociology and builds on the notion of capital – i.e. the accumulated and objectively available resources held by an individual (Bourdieu, 1986) – to explain human behavior within societal structures (Becker, 1975; Coleman, 1990). In this, scholars view capital and its distribution as the set of constraints under which society and individuals act (Bourdieu, 1986). As put forth by Bourdieu (1986) and Coleman (1990), two forms of capital are particularly notable from a sociological perspective, namely cultural and social capital. “Cultural capital” is defined as resources that are internal to individuals in the form of skills, knowledge, and capabilities that enable human activities (Coleman, 1990). “Social capital”, in contrast, commonly refers to the “resources embedded in a social structure that are mobilized in purposive action” (Lin, 2001), such as relatives, friends, or social institutions, such as governments and schools. In addition to cultural and social capital, sociologists also recognize an individual’s disposition – or “habitus” – as a key differentiating psychological resource for human behavior, and thus, as a type of capital (Bourdieu, 1990; Henry, 2004). These forms of capital and their application in IS research are summarized in Table 1.

In capital theory, one of the most intriguing features is the notion of conversion (Bourdieu, 1986; Coleman, 1990), which posits that one type of capital can be converted into or enhance another type (Silva, 2006). For example, cultural capital can be enhanced through the resources available within an individual’s social network (Bourdieu, 1984): users who lack the skills or competence to engage meaningfully with an Internet application may overcome this barrier by receiving support from someone from their social network. In other words, different forms of capital do not act in isolation, but rather interact with each other.

**Table 1. Forms of capital and their application in IS**

Capital	Definition	Application in IS	Supporting literature
Cultural capital	The resources that are internal to individuals in the form of skills, knowledge, and capabilities that enable human activities (Coleman, 1990)	<ul style="list-style-type: none"> <li>• Skills (formal, content)</li> <li>• Knowledge</li> <li>• Self-efficacy/ individual confidence</li> </ul>	Gui & Argentin, 2011; Hargittai & Hsieh, 2011; Kvasny & Keil, 2006, Hu et al., 2007; Reay, 2004
Social capital	The resources embedded in an individual's social structure that can be mobilized in purposive action (Lin, 2001)	<ul style="list-style-type: none"> <li>• Family, friends, relatives, peers</li> <li>• Support from managers, co-workers, employees</li> <li>• Social institutions, e.g. government, schools</li> </ul>	Wasko & Faraj, 2005; Hsieh et al., 2011; Chiu et al., 2006; Kvasny & Keil, 2006; Liao & Chou, 2012
Habitus	An individual's disposition towards an action or artefact (Bourdieu 1990; Henry 2004)	<ul style="list-style-type: none"> <li>• Perceived usefulness</li> <li>• Hedonic evaluation</li> </ul>	Davis, 1989; Norris, 2001; Venkatesh et al., 2003

Information systems research scholars have successfully borrowed and adapted constructs from capital theory to better understand variations in individual behaviors towards new technologies, under the premise that ICT use, similar to other human behaviors, is subject to capital constraints (De Haan, 2004; Rogers, 2003). For example, researchers have shown that the notion of cultural capital is indispensable for understanding *how* individuals use ICT (Gui & Argentin, 2011; Hargittai & Hsieh, 2011). Kvasny and Keil (2006) find that deficiencies in skills, knowledge and competencies limit an individual's ability to use cultural goods like ICT in the manner demanded by labor markets, governments, corporations and other institutions. Other ICT scholars have extended the notion of cultural capital to also embrace resources such as individual confidence and self-efficacy (Hsieh et al., 2011; Hu, Huhmann, & Hyman, 2007). These researchers found, for example, that such capital empowers an individual to activate available knowledge for action (Reay, 2004). Furthermore, social capital and related constructs, such as subjective norms, feature prominently in research on technology use (e.g. TAM, UTAUT) (Davis, 1989; Venkatesh et al., 2003). For instance, Chiu et al. (2006) explore the critical role of social capital on knowledge sharing in virtual communities. Additionally, scholars view an individual's general disposition or habitus towards ICT as one of the central determinants of individual tendency to engage with ICT (Davis, 1989; Norris, 2001). For instance, Davis et al. (1992) found that perceived usefulness and enjoyment significantly determine the intention to use, and usage of, computers in the workplace. Overall, IS research portrays habitus, cultural and social capital as influential in people's engagement with ICT (Hsieh et al., 2011; Kvasny & Keil, 2006; Warschauer, 2003). Economic capital, which for a

long time has reduced many people's access to ICT (De Haan, 2004), has become less of a bottleneck for ICT consumption in developed countries.

Leveraging the resource-based view of capital theory can help us to better understand which resources influence different stages of the appraisal and coping process and determine whether individuals engage with, or disengage from, Internet applications. Extant research suggests that the contextual and individual resources available to the individual, in form of habitus, cultural and social capital, can influence the appraisal and coping process by enhancing or limiting the individual's scope of action (Hsieh et al., 2011). For example, within the secondary appraisal phase, an individual under stress may evaluate his or her competence, social support, and the material resources at hand in order to readapt to the circumstances and to reestablish equilibrium between herself/himself and the environment (Schwarzer & Luszczynska, 2012). Yet several aspects remain unclear. For one, the conversion property of capital raises the question of how individuals leverage and convert their existing capital resources into the forms of capital that are particularly instrumental for their engagement with Internet applications, and what these are. For another, since the choice to engage with, or disengage from, an Internet application can be seen as an iterative decision process rather than a singular moment in time, different capital resources may be crucial at different stages of the decision process – yet it is unclear *which* resources are decisive and *when*. In this vein, we adopt a semi-exploratory approach to uncover the mechanisms that lead individuals to (dis-)engage with Internet applications and explore which types of capital resources play a critical role at different stages of the (dis-)engagement process.

### **3. Methodology**

Given the exploratory, process-oriented character of our research question and the complex and ambiguous nature of the mechanisms leading to (dis-)engagement (Selwyn, 2003), we employ a theory-informed, qualitative, process-focused case-research design (Eisenhardt, 1989; Langley, 1999; Yin, 2003). In this, we follow Conboy et al. (2012, p.117), who emphasize the ability of qualitative research to “extract key information [...] from a highly complex, uncertain, turbulent, multi-faceted context” and we answer repeated calls for more qualitative studies in information systems research (Venkatesh et al., 2013).

### **3.1 Case study context: Job search in the German labor market**

To induce an integrated middle-range theory (Merton, 1967) of the cognitive processes around user (dis-)engagement with Internet applications, we studied how job-seekers in Germany used Internet applications for their job search. The context of online job search is a uniquely suited empirical setting for our study for at least four reasons. First, how to search for jobs has dramatically changed over the last decade and the shift into the online sphere confronts individuals with the need to cope with multiple new Internet applications. Second, online job search constitutes a unique opportunity to study a critical case of (dis-)engagement with Internet applications, since individuals are highly involved and typically suffer from stress and uncertainty given the immediate social and economic consequences of unemployment – circumstances under which coping plays an important role. Third, the process of searching for a job spans over a certain period of time and as such promises to reveal individual variances in cognitive appraisals and outcome-dependent re-appraisal processes. Fourth, the German Federal Employment Agency (GFEA) plays a central role in the job search and placement process and is in personal contact with every individual who is or is facing unemployment. This provides a unique opportunity to study the influence of institutional social capital on user engagement.

In Germany, the means by which companies search for candidates to fill vacancies have changed dramatically with the rise of the Internet. While, in 2003, around 40% of vacancies of the 1000 largest German companies were still advertised in print media, this number has diminished to 12% in 2014 (Weitzel et al., 2015). Today, over 90% of the companies use online channels to advertise vacancies and search for employees (BITKOM, 2010; Weitzel et al., 2015). More importantly, the shift towards online channels has impacted the way actual placements are generated. For the 1000 largest companies, around 85% of placements are now generated through online channels (Weitzel et al., 2015). Even medium-sized companies nowadays generate 46% of their placements online, despite the fact that they rely more strongly on personal recommendations and the GFEA in their search for work force.

Generally, there are three main types of online job search applications: (1) company homepages, which job-seekers use to look for advertised vacancies, to search for information about potential employers, and to directly apply via an application interface. (2) Online job portals, which job-seekers visit to search for posted job offers or to post a “want” ad themselves. There are general online job portals, such as monster.de, as well as industry-specific job portals,

such as fashionunited.de. Job-seekers can narrow down their search using filter functions, for instance to focus on specific professions or locations. (3) Online social networking sites, which job-seekers may use to publish a professional profile, search for jobs and network. Most prevalent are professional social networking sites such as LinkedIn or Xing, however companies are also increasingly using popular social networking sites such as Facebook and Twitter to create awareness for vacancies.

While the online channel plays an increasingly important role in job search, offline channels such as print media, personal connections and the GFEA still play a role in the job search process. The first two are especially used by smaller companies to fill vacancies. A particularity of the German labor market is the GFEA, which acts as an agent between individuals seeking a job and employers seeking to fill vacancies. Individuals who become or are likely to become unemployed in the near future are obliged to attend a consultation meeting with an employment agent and fulfill certain requirements, e.g. to send out a minimum number of applications per month, in order to be eligible for financial aid. Conversely, companies can inform the GFEA about vacancies they want to fill. The matching process is then facilitated by the GFEA. The GFEA has adapted to the digitization of the job search sector and today offers a comprehensive online job portal, the possibility for job-seekers to publish a professional profile online, as well as a broad range of work-related information on their homepage.

### **3.2 Data collection**

In order to gain insight on how individuals engage with job-related Internet applications we collected a broad set of data – comprising interviews, self-tests of online job search applications, on-site observations and archival data – over a period of nine months from August 2014 to April 2015, as presented in Table 2. The multiple data sources served to triangulate and improve the trustworthiness of our analyses (Miles, Huberman, & Saldaña, 2013; Yin, 2003). First, we gathered statistics on the German online labor market and interviewed a recruiter of a large German company in order to develop an overview of the online job search applications available and used by employers. The authors obtained additional information about specific applications through self-tests. A visit of the GFEA and a face-to-face interview with one of the employment agents, which included a system demonstration, led to a good preliminary understanding of the interaction between the GFEA and job-seekers, as well as the level of information conveyed in a typical consultation meeting. We complemented this information by studying the user manuals on the GFEA's online job portal. Particularly the



Internet application self-tests and the personal encounters with the GFEA enabled the authors to assume a participant observer role by merging into the context of searching for a job themselves.

<b>Table 2. Data collection</b>	
Type of source	Data collected
Interviews	<ul style="list-style-type: none"><li>• 16 semi-structured interviews with individuals in the process of or recently looking for a job</li><li>• One interview with recruiter of a large German company</li><li>• One interview with GFEA employment agent</li></ul>
Self-tests	<ul style="list-style-type: none"><li>• Self-test of the ten most popular German online job portals</li><li>• Self-test of two most prevalent social network sites (Xing and LinkedIn)</li></ul>
On-site observations	<ul style="list-style-type: none"><li>• Visit of four branches of the GFEA</li><li>• GFEA system demonstration and study of GFEA user manuals</li></ul>
Archival data	<ul style="list-style-type: none"><li>• Statistics of the German Federal Employment Agency</li><li>• Research reports on recruiting trends covering 2003-2014</li><li>• Blogs and press releases on online job search applications covering 2010-2014</li></ul>

Second, and core to our data collection efforts, we conducted 16 semi-structured interviews with individuals who were currently or had recently been looking for a job. In line with Patton (2002), we used an interview guide approach because it is more open and flexible than a standardized interview approach, while at the same time ensuring comprehensive and systematic data collection. The interview guide is presented in Appendix A. All interviews were audio-taped and generally lasted 45-60 minutes. Additionally, demographic data and Internet use experience was collected from each interviewee. The interview protocol walked the interviewees back through the experience of searching for a job and we sought to minimize informant recall bias by using anchor questions (Collopy, 1996; Hufnagel & Conca, 1994).

A criterion-based, purposeful sampling (Patton, 2002) was used for this study in that we selected only participants who were currently or had recently been seeking a job in order to maximize “information-rich” cases (1990, p. 169). Following Miles et al. (2013) and Trost (1986), we tried to maximize variation by sampling participants from different educational backgrounds, age groups, gender and urban/rural places of residence. For example, Josh (29) was released after five years in prison and was in the process of seeking an apprenticeship to become an electrician in Berlin, while Lisa (59) lost her job at the age of 57 and was struggling to find a position as an office clerk around rural Düren. Participant information is displayed in Table 3. Sampling was done iteratively (Miles et al., 2013) to allow for emerging patterns in the data to be challenged (Clarke, 2005; Strauss & Corbin, 1990). Interviews were conducted

and simultaneously analyzed until additional interviews only repeated already identified themes, indicating a point of theoretical saturation (Yin, 2003). All interviews were transcribed *in vivo*, yielding 182 pages of field notes.

**Table 3. Interviewee demographics<sup>22</sup>**

Name	Gender	Age	Highest attained degree of education	Focus of job search	City	Internet use frequency
Judy	Female	32	Vocational training	Media design	Berlin	Daily
Paul	Male	37	Vocational training	Social work	Berlin	Daily
Cait	Female	44	Bachelor degree	Social work and stage/costume design	Berlin	Daily
Lisa	Female	59	Vocational training	Office clerk or field service	Düren	Several times per week
John	Male	26	Vocational training	Shop assistance	Berlin	Daily
Pete	Male	44	Master degree	Project management	Berlin	Daily
Dave	Male	33	Master degree	Software programming	Berlin	Daily
Matt	Male	39	Master degree	Art history	Berlin	Daily
Anna	Female	33	Vocational training	Shop assistance or interior decoration	Berlin	Several times per week
Henry	Male	28	Vocational training	Automotive sales	Düren	Daily
Kevin	Male	43	Vocational training	Retail sales	Berlin	Daily
Mary	Female	63	Vocational training	Florist or caretaking	Düren	Never
Mike	Male	24	Vocational training	Social care work	Düren	Daily
Carl	Male	39	Certificate of Secondary Education	Construction work	Berlin	Daily
Tom	Male	23	Certificate of Secondary Education	Goldsmith or security guard	Düren	Daily
Josh	Male	29	Certificate of Secondary Education	Messenger or electrician	Berlin	Daily

### 3.3 Data analysis

Content analysis was conducted in an iterative process based on coding techniques proposed by Strauss and Corbin (1990). This approach enables the researcher to verify existing theoretical concepts and to discover new, emerging concepts at the same time (Lincoln & Denzin, 2000). Coding was conducted in two steps<sup>23</sup>: open coding and axial coding. First, in the open coding phase, transcripts were analyzed line by line and coded based on an a priori developed coding book informed by the theoretical constructs of coping and capital theory (Strauss & Corbin, 1990). This was combined with a purely inductive open-ended analysis,

<sup>22</sup> Displayed in the temporal order of interviews. Names were altered to keep participant information anonymous.

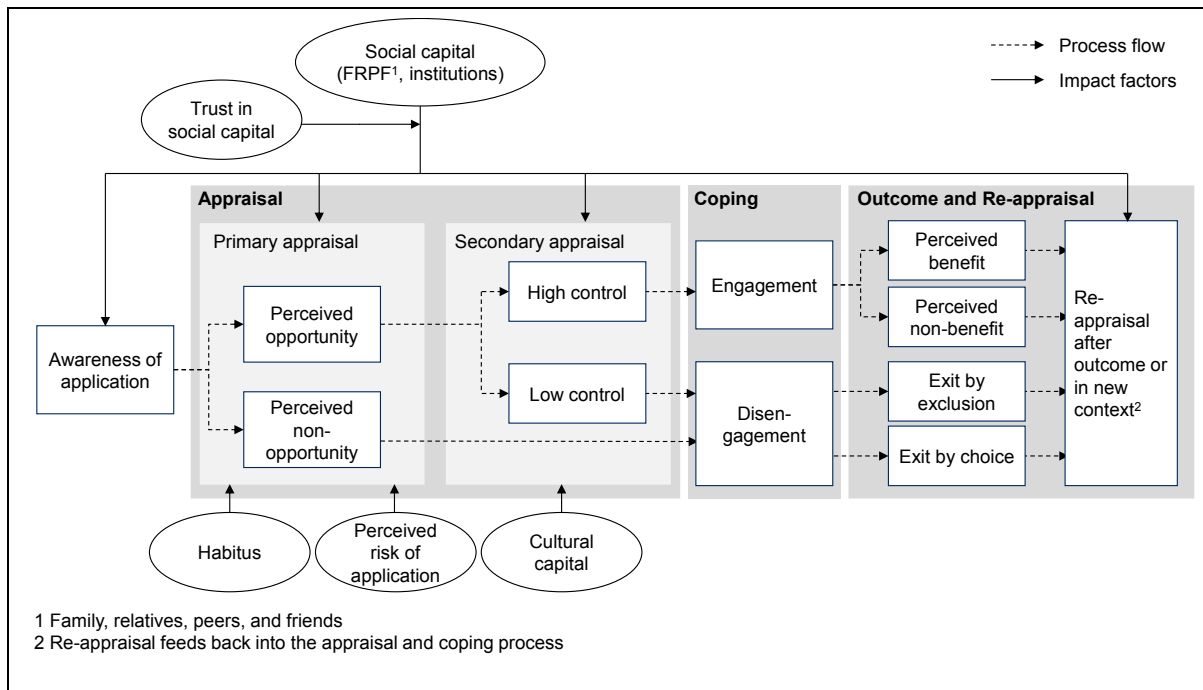
<sup>23</sup> Complete coding guidelines can be obtained from the authors

allowing for new themes to emerge. As proposed by Miles et al. (2013), two of the researchers coded pairs of interviews independently from each other and compared their results. On average, inter-coder reliability between the two raters was 92%. In total, 53 deviating classifications were discussed and resolved. This approach was repeated for each set of interviews throughout the complete coding process to ensure full inter-coder agreement.

Second, axial coding was applied in order to disaggregate and reassemble data in order to focus on the relationships between and within categories (Strauss & Corbin, 1990). In order to establish these relationships – e.g. context conditions, causal conditions – codes were grouped in sub-categories and categories around emerging relational themes. The coding assignment was continuously revised, abstracted, and consolidated in an iterative process until full inter-code agreement was achieved on all dimensions. The entire coding process generated a total of 656 coded *in vivo* quotes, 239 first-order codes and 48 second-order codes clustered within eight overarching categories. The coding structure and examples of the coding procedure are provided in Appendix B.

#### **4. Results**

Figure 2 visualizes our emerging understanding of the coping mechanisms that lead to (dis-)engagement with Internet applications and the impact of individual capital resources at different stages of the process, as induced from our interviews. Below, we present our model along the steps leading to engagement or disengagement. We start by illuminating the individual's appraisal of Internet applications, which begins with his or her awareness and is followed by the primary and the secondary appraisal. We then reflect about coping, outcomes, and re-appraisal of Internet applications. At each stage, we illuminate the emerging relational impact of individual capital resources on appraisal and coping, and, where applicable, present additional factors induced from the data, such as perceived risk. By extension, we discuss how the individual's trust in social capital moderates the influence of social capital on the appraisal of Internet applications. It should be acknowledged that, in practice, the different stages of the coping process, in particular the appraisal phase, are not always explicitly distinct but rather part of a fluid, iterative cognitive process. In the interest of clarity, we present the results in a relatively deductive style even though they were generated inductively (Gioia & Chittipeddi, 1991).



**Figure 2. The impact of individual resources on the coping process**

#### 4.1 Awareness of Internet applications

Awareness of Internet applications is by definition a prerequisite for appraising an application as an opportunity or non-opportunity. Interestingly, we observed that the quality of awareness for online job search applications differed greatly among our interviewees. For instance Pete, a graphics project manager, was aware of a large range of job portals such as Monster.de and professional networking sites such as Xing.de, and was well informed about the differences between these applications. He noted, *“There are really different offers on Morgenpost.de compared to Gigajobs.de, that’s why I use them both [...] and I also use the ‘Eye’, a highly specialized site in the field of web design.”* In contrast, Josh, who wants to become an electrician, knew Google, but no specifically job-related Internet applications.

Our interviews indicate that limited awareness not only constrains people’s opportunity consideration set but may also affect their primary appraisal. In this regard, we found that some respondents drew inadvertent conclusions about their usefulness because they were only tangentially aware of online job search applications. Matt, for instance, knew little about the professional networking site Xing and, based on this limited information, believed that it was not suitable for him as a *“young professional directly from college with little experience.”* In other words, he did not recognize that, in reality, Xing is a professional platform for both young and experienced professionals, which led him to believe that it is not an opportunity for him.

Moreover, we observed that respondents with tangential awareness of online job search applications felt insecure whether to evaluate an application as an opportunity or non-opportunity because they felt they lacked the informational basis to do so. For example, Paul mentioned that the only application he knew where it is possible to have a profile is Xing, but because he did not feel well versed in this field of applications, he refrained from engaging with it: *“Unfortunately, I don’t know any other professional networking sites besides Xing. As such, I don’t even know what other possibilities there are. If I knew more options, I would potentially try one.”*

Next, our observations reveal that the interviewees reverted to two sources of awareness, namely they themselves and their social capital. Some interviewees became aware as a combination of their own active search and serendipity. Dave, for example, became aware of a specialized job portal for front-end developers by *“stumbling on some blog posts which mentioned that people twitter jobs [...] Then, I looked on Twitter for jobs and found this job portal.”* In contrast, others – the majority in fact – referred to the vital role of social capital – their family, friends, and peers, as well as educational and employment institutions – in making them aware of online job search applications. This was particularly the case for those interviewees who lacked the ability or motivation to search for new applications by themselves. For example, Judy was unemployed for the first time and only knew a few online job search applications. Therefore she relied heavily on support from friends, which is how she became aware of eBay Classifieds as a potential search channel: *“I didn’t know about it beforehand. I heard about it from a friend, who said: why don’t you look on eBay Classifieds? I would never have thought of it myself, to be honest.”*

Intriguingly, our findings also indicate that the impact of social capital is not exclusively positive but that social capital is in fact a double edged sword. In this regard, some interviewees noted that the people in their social network could not help them in using online job search applications. Henry, for example, talked with colleagues about his difficulties in finding a job as an automotive sales rep but said that they *“only had the same ideas”* as himself. In other words, our findings suggest that the more the awareness structure among someone’s social capital resembles his or her own awareness structure, the less likely it is that the individual will receive new stimuli. These findings are in line with Granovetter’s (1973) notions of weak ties, which suggests that a heterogeneous network of acquaintances may be more helpful in many cases than a homogeneous network of close friends. Additionally, we observed that

institutional social capital, which could be expected to counter this effect, often exacerbates the potential downsides by further constraining the set of opportunity considerations. John, for example, voiced his disappointment that the GFEA “*only recommends its proprietary job portal*” and fails to inform about the breadth of online job search options available. We found that this had a particularly severe impact on those individuals who relied heavily on the advice from institutions like the GFEA and whose awareness and subsequent engagement was almost exclusively determined by, and limited to, the impulses they received.

In summary, awareness of Internet applications not only differs greatly among individuals, but also impacts the primary appraisal, particularly by limiting the opportunity consideration set or promoting the assessment as non-opportunity. Moreover, not just the individual itself but, more importantly, social capital can extend the awareness for online applications. The role of institutional social capital is especially critical in this context as individuals with homogeneous social capital networks can only get new impulses from social capital outside of their network. Particularly because institutional social capital has a formal role and individuals perceive it as highly legitimate to follow its advice, institutional social capital can turn dysfunctional if it creates awareness only for a small set of applications.

#### **4.2 Primary appraisal of Internet applications**

As part of their primary appraisal, individuals assess whether they believe an Internet application is relevant for them or not. Two main categories of primary appraisal emerged from our interviews, which we termed *perceived opportunity* and *perceived non-opportunity*<sup>24</sup>. Individuals who perceived an online job search application as appropriate, interesting, or useful considered it as an opportunity, which means that their engagement depended on their subsequent secondary appraisal. Conversely, individuals who did not perceive an application to be relevant to them appraised it as a non-opportunity and disengaged from it. Our interviewees mentioned three factors that particularly influenced their primary appraisal as a perceived opportunity or non-opportunity: habitus, perceived risk, and social capital.

Individual habitus comprises the perceived usefulness of an Internet application and the degree to which individuals enjoy using an Internet application, i.e. their hedonic evaluation. Our

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<sup>24</sup> The findings indicate that in a quasi-mandatory setting – where an individual is not forced but expected to use a technology – such as job search, individuals appraise applications either as an opportunity or as a non-opportunity. While some individuals express feeling obliged by social conventions or institutions to use Internet applications for their job search, they do not perceive these expectations as a “threat” (Lazarus & Folkman, 1984), given that viable offline alternatives exist.

findings indicate that in the context of online job search, the effect of habitus on primary appraisal manifested itself almost exclusively in terms of how useful respondents believed an Internet application would be for their job search in terms of value add and opportunity cost. Pete, for example, was willing to pay extra for a premium account on a professional networking site because he perceived the additional information he could access and the messaging service as highly valuable. Moreover, referring to Stepstone, he noted, *“I like[d] the forwarding option [...] and what was cool, was that when you click on a job, you are shown other, similar positions.”* Hedonic aspects, in turn, played a very minor role in respondents’ primary appraisal, which is not surprising in the context of a predominantly utilitarian application such as online job search. Overall, in their appraisal, active respondents like Pete often compared different applications to determine which they found more useful (or enjoyable). We induced from this observation that the consideration set initiated through awareness determines the frame of reference within which individuals appraise applications as opportunity or non-opportunity.

Perceived risk emerged as a second important factor for primary appraisal. Matt, for instance, recounted how he searched for a job on several job portals that seemed promising but required a free registration to access the job descriptions. He decided not to pursue them further because *“I was bothered by the personal data that I had to provide at the start [and because] I didn’t want to disclose all my personal information.”* Our observations indicate that all but two respondents were concerned about data security issues. Individuals who generally disliked sharing personal data online were particularly sensitive to this aspect and more likely to appraise an application as a non-opportunity if it required them to provide data. Another factor that respondents were worried about was the reliability of online job ads. In particular, some respondents had made bad experiences with ads that were not up-to-date and, in turn, gravitated towards viewing job portals as a non-opportunity that provided imprecise or incomplete information.

More apparently even than habitus and perceived risk, the primary appraisal of online job search applications was impacted by social capital. In fact, the majority of respondents relied on input from their social network, particularly when appraising a new application for the first time. Our data indicates that the more proximate and tangible an individual’s social resources, the stronger their influence on the primary appraisal. Mike, for example, decided to try out the GFEA job portal because *“it’s what everyone knows, [...] it’s what everyone uses,”* thereby

catering to subjective norms of his social environment. Beyond this, many interviewees indicated that actual positive experiences with the application by relatives and friends had an even greater effect. Lisa, for instance, decided to try out a professional networking site after she *“heard from a friend, who tried it and found a job over it.”* Similarly, Matt explained that he has *“some friends [who] use Xing, and one friend even received a top job offer through it,”* which led him to appraise it as an opportunity. And Kevin, for example, followed the suggestions of a friend who *“explained the whole [online job search] system to me and told me: you can look here and then try this [portal].”*

As with awareness, the influence of social capital seemed to be not uniformly positive. In this context, Pete acknowledged that *“most of [his] friends and acquaintances use the same [online job search] strategies as [him],”* which is why he did not rely on them for new impulses but rather tried to find his own way. Those respondents who relied strongly on the advice they received from others ran the risk of being limited by that advice. Judy, for instance, considered only those three applications as opportunities that were explicitly recommended to her by the GFEA and her friend, thereby limiting her consideration set: *“I really just used the three platforms I mentioned: Google, the GFEA portal and eBay Classifieds.”*

In summary, our findings indicate that the primary appraisal of an Internet application is determined not just by habitus but also by perceived risk and social capital. Perceived risk may counter aspects like perceived usefulness and enjoyment and lead an individual to appraise an application as a non-opportunity. More interestingly, social capital seems to play a pivotal role in determining which applications potential users perceive as an opportunity, in fact, to an extent that goes beyond subjective norm. It may, however, not just extend but also limit the set of applications that is appraised positively.

### **4.3 Secondary appraisal of Internet applications**

Besides appraising whether they considered an Internet application an opportunity for their job search, our interviewees also assessed the degree to which they perceived they could exert control over the application. Henry, for example, felt confident about compiling documents and sending out online applications and noted *“that is easy for me”* but, he struggled to navigate multiple job portals and to *“find fitting job postings in this excess supply.”* The interviews revealed that the interviewees primarily referred to two forms of capital when assessing their level of control over an application: first, cultural capital comprising medium-related skills, content-related skills and self-efficacy; and second, social capital.



#### **4.3.1 Secondary appraisal and cultural capital**

Medium-related skills encompass basic operational skills, such as operating a browser or search engine, as well as formal skills, such as the ability to navigate within and between websites by using hyperlinks and menus (van Deursen & van Dijk, 2011). Interestingly, it emerged from the interviews that only very few participants did not exhibit the required medium-related skills to formally operate various online job search applications. In other words, medium-related skills did not seem to be an inhibiting factor and sufficed to gain a feeling of control over simple applications and tasks.

In contrast, when it came to not just formally operating, but effectively *using* online job search applications in a goal-oriented manner, content-related skills emerged as a crucial factor in determining how much control the interviewees perceived. Content-related skills comprise information skills, such as defining meaningful search queries and evaluating information, as well as strategic skills, that is, the ability to efficiently and effectively take advantage of Internet applications to reach a particular goal, such as finding job (van Deursen & van Dijk, 2011). The interviews highlighted the critical role of these content-related skills for being able to navigate the multiple opportunities of online job search. Many respondents reported that they valued the increased range of options made available through online job search applications but also felt that it had become increasingly complex. Pete, for instance, struggled with the multitude of job ads available on the job portal site Stepstone.de: *“I find myself sitting in front of Stepstone for over an hour and I feel like it’s not getting better. I feel like it’s getting more and more complex.”* Similarly Paul, a social worker, noted that he found it *“very difficult to filter out the really fitting job postings”* amongst the deluge of postings his search generated. The interviews highlighted that the sheer amount of information available online necessitates the ability to keep an overview and intelligently select and assess the options at hand.

Our observations indicated that particularly those interviewees with limited content-related skills easily felt confused and overloaded in their online job search, which led to frustration and ultimately disengagement. Those who lacked the ability or strategy to actively steer their online job search process tended to get lost in the sea of information and options and spend a lot of time drifting aimlessly without getting to any results. Cait, for example, reflected that even though she perceived online job postings as an opportunity, she was unable to effectively make use of them: *“It interests me to see what’s on offer online, so I start looking, and I look a lot. I think it’s good that it exists, but I have trouble disciplining myself. I can completely lose*

*myself.*” Because she was unable to gain control of the situation she eventually disengaged and retreated to using only those few applications she felt comfortable with.

Interestingly, even respondents with a high level of content-related skills became frustrated when they felt constrained by an application structure or interface and had the impression that they could not meaningfully control the application. As a result, they either disengaged or they used their skills to deal with the problem and found a workaround. For example Dave, a software programmer, refused to use the GFEA job portal menu because, as he stated, he perceived it to be *“a total mess compared to other job portals.”* However, he was able to find a workaround: *“I prefer to type into Google what I am looking for and then find the sublink for a certain page of the GFEA job portal – to navigate through their menu is just not reasonable.”* Other interviewees critiqued that the pre-configured job categories did not match their own search needs.

Lastly in this regard, our interviews showed that, apart from skills, self-efficacy can act as a differentiating factor and compensate for, or enhance, the impact of skills. In our coding, we borrowed the term “self-efficacy” (Bandura & Locke, 2003) to denote an individual’s belief in his/her capabilities to use an Internet application. We observed that respondents who lacked the medium- or content-related skills to leverage an application were able to overcome this limitation if they had high self-efficacy. Conversely, respondents with low self-efficacy felt inhibited to try an application despite potentially having the skills to do so. For instance, Anna exhibited rather limited skills, however this did not stop her from exploring new applications: *“I am still trying to figure out what I can use. From time to time I just go to the GFEA site and look for occupational re-trainings or even just educational offers like an English course.”*

#### ***4.3.2 Secondary appraisal and social capital***

Importantly, our findings suggest that social capital can also have a critical impact on secondary appraisal, particularly by changing a feeling of low control to one of high control. Tom, for instance, struggled with the online application process for a position but did not disengage because he had friends to support him: *“I found it too complicated, I couldn’t get to grips with it myself, so I mostly did it together with friends.”* Apparently, in cases like Tom’s, social capital compensates for an individual’s low cultural capital by providing an external source of knowledge and support. Interestingly, we observed that in some cases *theoretical* access to social capital sufficed to secure engagement. For example, when asked to reflect on whether he would be able to send out an online application, Mike did not immediately reject the idea–

despite not knowing how to go about it—because he knew whom to ask for help: *“I think I would ask my dad. I think he would be able to help me because he uses computers a lot at his work.”*

Our observations indicate that institutional social capital takes on a particularly important role where personal social capital, such as family and friends, reaches its limits. Respondents with high control of their online job search or personal networks that offered help did not need and typically did not seek institutional support. In contrast, many respondents with low control and personal networks that could not offer much help wished for stronger institutional advice in terms of which job portals to search on or how to create a professional profile. Lisa, for instance, could not draw on much help within her personal social network and had hoped to receive more guidance from her job agent: *“When [the GFEA agent] tells you: here is a list, you need to send out 20 applications, five a week, just look them up and give them a call – I find that too little help. That’s not enough.”*

Similar to primary appraisal, social capital can have not just functional but also dysfunctional effects. By trying to facilitate the online job search process by taking over tasks rather than supporting capability building, institutional social capital can promote dependency. Many respondents indicated that they would have preferred to get enabled and *“leave the institution with the feeling that you can go home, sit down and know where to look and what to do”* (Lisa) rather than have institutions take over the tasks for them. In some cases, the expectation of help from and reliance on institutions was so strong that individuals became very passive in their own (online) job search, as was the case for Judy: *“Maybe I should have done something completely different, [...] but the employment agent didn’t mention anything. So I thought: ok, it’s probably not possible. [...] It was a bit naive.”*

In summary, it seems that during secondary appraisal individuals perceive to have high control over Internet applications if they exhibit a sufficient level of content-related skills and self-efficacy while medium-related skills rather seem to be a hygiene factor widely observable among the interviewees. Interestingly, social capital can compensate for an individual’s limited skills or self-efficacy by giving advice, teaching and constituting a (theoretical) fallback option for support, thereby translating a feeling of low control to high control. Particularly in the case of institutional capital there seems to be a fine line between facilitating online job search and promoting dependency by taking over tasks for the individual.

#### **4.4 Coping, outcomes and re-appraisal of Internet applications**

Based on their appraisal of an application, our respondents engaged with or disengaged from the respective application. In case of engagement, respondents coped by using the online job search application while drawing on the capital resources available to them. Lisa, for example, managed to send out applications by email after reaching out to her friend for support. In case of disengagement, we found that respondents did not use the application and focused their behavioral and cognitive efforts on re-framing the situation to justify their disengagement rather than undertaking steps to make engagement possible. Mary, for instance, justified her decision to not use the Internet for her job search by saying “*I do not need it [...] I also don't see when I am supposed to use it.*”

We observed two possible outcomes of engagement: perceived benefit and perceived non-benefit. Our findings suggest that respondents evaluated the outcome of their engagement primarily based on their satisfaction with the content (e.g. did the job postings match their expectations), their satisfaction with the interface of the application (e.g. did it facilitate the job search), and whether they eventually found a job through the Internet application. For instance, Mike mentioned that he “*searched on meinestadt.de, but I did not find anything. Therefore I did not continue to search there.*” Similarly, Dave evaluated the outcome of using a job portal as follows: “*You find a lot of information on this site but [...] the page interface is structured in such a way that I would not use it to search for jobs again.*”

A number of respondents disengaged from an Internet application as a result of a deliberate withdrawal – in other words, an exit by choice. We observed that some individuals subjectively perceived an online job search application to be a non-opportunity in the primary appraisal phase – even though they may actually have benefited from using the application – and chose to disengage. Others objectively would not have benefited from the application, like Carl, who works in construction where personal connections are more important than the Internet for finding work: “*I always found a job. Always through connections, compatriots: you know somebody and he knows you. Never the Internet.*”

More importantly, however, we observed that some respondents appraised an application as a perceived opportunity, but lacked the resources to gain sufficient control of it and disengaged as a result – in other words an inadvertent withdrawal, or exit by exclusion. Cait, for example, felt that certain applications could help her in her job search but was so overwhelmed by these applications that she could not continue engaging with them: “*The Internet certainly helps to*

*find them [social work institutions]. [...] But I really do not like it, I really feel that I am not good at it, I get cold feet, my head starts spinning, and often I spend a lot of time online but I do not find anything truly relevant for me.*” The key difference between an exit by exclusion and an exit by choice lies in the willingness to try and engage with the Internet application, and the subsequent failure to do so due to low control. An exit by exclusion may not always be apparent because individuals tend to focus their behavioral and cognitive efforts on re-framing the situation to justify their disengagement. Based on our observations, they most commonly do so by rescinding their primary appraisal and professing that the application in question is not actually useful.

The findings suggest that the nature of the outcome influences the re-appraisal of the application and, consequently, future use by reinforcing behavioral patterns in case of beneficial outcomes and by fostering disengagement in case of non-beneficial outcomes. In many cases the first experience with an application was already decisive for future use. John, for example, stated: *“I hardly used Google because I already knew meinestadt.de from six years ago. So far it has worked well for me.”* We further observed that, independent of the perceived outcome, external impulses could play a key role in triggering the re-appraisal of an application – particularly those stemming from respondents’ social capital. Paul, for instance, initially disengaged from using online profiles on professional networking sites but re-appraised the application positively following an impulse from a friend: *“A friend just purchased a premium Xing account and directly received several requests. So when I search again, I might just try it as well.”*

In summary, having reached the end of the coping process, we see the overarching mechanisms of engagement and disengagement that emerge as a result of the appraisal process and the influence of various capital resources thereupon. Individuals who perceive an Internet application as an opportunity and have the means to control it typically engage, resulting in either a perceived benefit or non-benefit. Meanwhile, those individuals who are unable to control the application meaningfully or perceive it as a non-opportunity tend to disengage, resulting in an exit by exclusion or exit by choice respectively. Crucially, the decisive role in determining which mechanism plays out typically falls to an individual’s resources, such as social or cultural capital.

#### **4.5 The moderating effect of trust on social capital**

Our findings suggest that social capital can have both a limiting and enhancing effect on an individual's awareness and appraisal of Internet applications. The directional impact of social capital, however, appears to be moderated by an individual's trust in it. We observed that many respondents implicitly or explicitly evaluated whether they considered their social capital a trustworthy source of support. This evaluation, in turn, influenced to which degree these respondents were receptive for impulses coming from these social capital sources. These findings support the notion that trust constitutes as an integral part within the relational dimension of social capital, as posited by Nahapiet and Ghoshal (1998). We will focus on institutional social capital since the topic of trust appeared to be more crucial with regard to institutions rather than family and friends. We observed that respondents primarily considered five factors when evaluating the trustworthiness of institutional social capital: perceived competence, perceived authenticity, perceived image, perceived pressure, and perceived appreciation. While the majority of respondents reported negative experiences it is important to note that these five factors can also have a positive impact on trust.

Several respondents perceived employment agency institutions to lack the competencies that they considered to be important in supporting their job search, such as knowledge about different professions and online job search applications. Even though they mostly drew their impressions from one or two personal encounters with employment agents or even just hearsay, they tended to transfer their impressions onto the whole institution, including its online offerings and its advice. For example, Mike recounted an initial consultation meeting at the GFEA in which *"the job agent had no idea of occupational titles and I had to explain everything."* He found that *"quite dubious"* and, convinced that the job agent was incompetent, was very skeptical of the suggestions he received.

Furthermore, we observed that a number of respondents were concerned that the employment agents were not sincere in their assignment to help them find a job. Kevin, for instance, felt that the employment agents were *"just sitting there and really do not care,"* while Tom had the impression that *"those professional trainings they offer [...] are just means of deferral"* to keep him out of the unemployment statistics. Moreover, John expressed doubts regarding the agency's willingness to truly help him with his job search because he felt that the agents were incentivized to only recommend their proprietary online job portal: *"They just say 'search the web', 'use our job portal'; they do not say 'search on this or this specific website' [...] I do not*

know how it actually works, if they still get their rewards from the state when they place somebody through an Internet portal other than their own...Of course they only recommend their own job portal." All these doubts about the employment agency's authenticity made the affected respondents less receptive for impulses coming from that source.

Independent from actual personal experiences, we found that some respondents already had a preconceived notion of the GFEA based on their perception of its public image. In particular, these respondents believed that companies primarily use the GFEA online job portal to advertise low skilled jobs, which is why they perceived the GFEA's online job portal as a non-opportunity for themselves. Kevin, for example, stated: *"I do not know any firms which use the GFEA to search for qualified people, only the desperate. Over the last 20 years a certain cliché has evolved about the GFEA that you only get the ones you do not want. I believe that everybody who seriously wants to find a job will not find a cool job through the GFEA."* As a result of this preconceived notion, many were afraid that their application would be evaluated less favorably by employers if it was facilitated through the GFEA's online job portal.

We further observed that a few interviewees expressed feeling pressured by the employment agency. Lisa and her husband, for example, struggled to meet the application targets set by their job agent because it took them a long time to get acquainted with online job search, given that they are in their late 50s and were doing this for the first time. Instead of receiving support, they were reprimanded, which left them even more insecure and eventually made them retreat to using only newspapers for their job search. As Lisa puts it: *"There are many people who get rebuked for not having done anything, but in fact, most of them do not even know what to do or where to search for jobs and how it actually works."* This suggests that particularly for those individuals with low control of their online job search, lack of support and pressure by an employment agent can deepen the feeling of low control rather than help bridge it.

Lastly, our observations indicate that the perceived appreciation experienced by respondents in their consultation meetings with job agents influenced the degree to which they trusted them. For example, Kevin decided that he would *"not involve the GFEA again when searching for a job"* because he was asked to apply for a job which he – as he put it – *"could do with one hand tied behind my back."* Similarly, Cait did not feel appreciated in her first consultation meeting: *"First they told me: everything you did was wrong. You do not have a degree, and I cannot even place those with a degree and your background. I will find you a job as a waitress."* Many

respondents felt offended and written off when the agents recommended jobs that they perceived to be way below their skill level.

While this narrative appears to be dominated by negative experiences, it is important to note that this is not surprising given the burdensome context of unemployment and a natural tendency to voice concerns rather than praise. Nevertheless, some interviewees also shared positive experiences. Matt, for example, valued the objectivity and sincerity of employment agents who told him *“clearly and objectively”* to consider a professional reorientation and Henry perceived the GFEA and their online offerings to be of great help for his job search: *“The job agent could not have received me more friendly or kindly, she was really helpful.”* Respondents with positive experiences, like Matt and Henry, showed a greater level of trust in institutional social capital and were more receptive for impulses coming from that source.

## **5. Discussion**

In this study, we sought to better understand individual (dis-)engagement with Internet applications. By leveraging coping theory as a theoretical foundation, we embrace the dynamic nature of the decision to engage with, or disengage from, a technology and unveil how individual resources impact different stages of this iterative process. Most importantly, our findings show that the pathways through which individuals appraise Internet applications are significantly influenced by the capital resources available to them. In particular, our model reveals that social capital is effective at every step of the cognitive appraisal process, while habitus, perceived risk and cultural capital only impact a single stage. In fact, social capital can trigger awareness, change individual dispositions, and be converted into cultural capital. As such, it plays a game-changing role that can determine individual engagement or disengagement. Moreover, we find that the power of social capital to foster engagement is a function of the trust that the individual has in his or her social capital.

Our findings on why, and through which mechanisms, individuals engage with, or disengage from, Internet applications particularly contribute to research on technology use and adoption (Burton-Jones & Grange, 2012; Hsieh et al., 2011; Venkatesh et al., 2012). Responding to calls to investigate alternative theoretical perspectives on technology acceptance in order to broaden the field's understanding towards a wider constellation of behavioral responses (Abraham et al., 2013; Schwarz & Chin, 2007; Venkatesh et al., 2007) and for a greater dialogue between divisions of related research (Yu, 2011), we take a dynamic perspective on technology use and non-use by building on coping theory and relating aspects of capital theory to the individual



resources influencing different stages of the coping process. We further enrich the resulting model with the constructs of awareness, perceived risk of Internet applications, trust in social capital, and a differentiated perspective on skills and show how these play a critical role at different stages of the coping process. In contrast to most extant research on technology acceptance (TAM, UTAUT, etc.), this study explicitly incorporates the dynamic nature of user (dis-)engagement, yielding a more multi-faceted understanding of technology use. In particular, the developed model uncovers how different forms of resources can enhance and substitute each other at *every* step of the cognitive appraisal process. This extends our understanding of the role resources play at different stages of the coping process, which has previously considered capital resources to be most relevant for secondary appraisal (Lazarus & Folkman, 1984). In line with calls for further research on capital conversion (Hsieh et al., 2011), we also contribute to capital theory by highlighting how and when different forms of capital can be converted into resources that are instrumental to (dis-)engagement with Internet applications. Grounding (dis-)engagement with Internet applications within a cognitive appraisal process and identifying the impact of different types of resources at different stages of this process helps to better understand and predict individual user behavior and ways to influence it.

Furthermore, this research reveals the game changing role social capital and in particular institutional social capital can play for individual engagement with Internet applications. So far, little research has been dedicated to understanding how and under which circumstances social capital can be converted into forms of capital instrumental to technology acceptance (Hsieh et al., 2011). This study sheds light on how social capital can compensate for risk factors that favor disengagement, such as limited awareness and low control, as well as the preconditions in terms of trust that need to be present. In contrast to most technology use research that acknowledges trust as an important factor but examines it with regard to the focal technology (e.g. Gefen et al. 2008), our findings suggest that trust also plays an important moderating role on the effectiveness of social capital. Furthermore, our results show that social capital does not necessarily only foster engagement but can indeed also impede engagement, for instance by limiting the consideration set of appraised options. IS researchers should take care to consider this potentially adverse impact of social capital on engagement rather than portraying social capital as uniformly positive. Moreover, our research provides new and contrarian insights into the role institutional social capital can play on technology acceptance. Social capital relating to friends, family and peers is a well-known factor in traditional

technology acceptance models, however, institutional social capital has often not been explicitly considered (e.g. Venkatesh and Brown 2001; Venkatesh et al. 2012) or has been found to play only a minor or insignificant role for technology use (e.g. Hsieh et al. 2008). Our model shows that institutional social capital can indeed impact technology use provided that a trusted set-up exists that enables directed measures to be implemented, e.g. through government agencies or schools.

Following calls for more in-depth qualitative research (Selwyn, 2003; Venkatesh et al., 2013), this study also contributes to broadening and complementing the methodological foundation for understanding the phenomenon of technology use and non-use. Qualitative research still constitutes an underused method for investigating technology use yet is necessary to meaningfully extend and enrich our understanding of the underlying mechanisms of use and non-use. This study underlines the necessity of a qualitative approach in order to grasp the complexity, the dynamism and the multitude of pathways that may lead to technology (dis-)engagement – aspects that are unlikely to be captured in the same richness and depth through traditional, survey-based research.

In addition, by drawing on sociology and communication research we introduce a new, more differentiated perspective on Internet skills – comprising medium- and content-related skills (van Deursen & van Dijk, 2011) – into the technology use discussion. Skills have been acknowledged as an important factor for technology use and have mostly been conceptualized as part of constructs such as perceived ease of use or perceived behavioral control (Venkatesh et al., 2003). A more differentiated view on skills is necessary to understand how exactly skills foster or impede technology use. This notion is especially important given that both the skill levels in the population and the skill requirements for effective Internet use are constantly evolving. Our findings show that medium-related skills are in fact widely present yet content-related skills are required to effectively navigate and evaluate the manifold online options available to accomplish a certain task.

Finally, this study also contributes to research on digital inequality and to the debate on how digital gaps can be bridged (Hargittai & Hinnant, 2008; Kvasny & Keil, 2006). Our research highlights the factors that lead to undesirable outcomes, such as inadvertent digital exclusion, and helps to explain why digital inequality is still a prevalent issue even in developed countries with widespread Internet access. Most notably, our findings emphasize that limited awareness, insufficient content-related skills, and lack of social support are nowadays much more critical

factors for digital exclusion than Internet access and medium-related skills, which have been the focus of extant digital inequality research. Further, our study shows that institutional social capital plays a particularly important role for the digitally disadvantaged since these individuals rely strongly on support from family and friends (Hsieh et al., 2011), yet typically have fairly homogeneous personal social networks (Granovetter, 1973; Yu, 2011). This limits the potential value add they can draw from their personal social capital and calls attention to the importance of governmental institutions in helping individuals overcome this barrier. Particularly the insights on how institutional capital may be able to influence the cognitive appraisal of Internet applications – e.g. by raising awareness and supporting capability building – represent an important contribution to the stream of research focusing on how digital gaps may be bridged through governmental interventions.

This study also has important implications for public policy and managerial practice. With the ongoing digitization, it becomes imperative for governments to ensure digital inclusion both as a social mandate and – against the backdrop of increasing e-government services – in their own interest. In particular, this study can help policy makers to better understand why people take or do not take part in the ongoing digitization and most importantly, to define targeted policy interventions aimed at fostering digital inclusion. These policy measures need to focus enablement in order to meaningfully empower the digitally disadvantaged to independently use Internet applications. Policy makers can leverage the pivotal role of institutional social capital in their intervention planning, e.g. by further integrating digital education into curriculums and by identifying governmental institutions that are best suited to convey targeted support to individuals. Additionally, our research shows that trainings should ideally raise targeted awareness and teach not just medium-related skills but, more importantly, content-related skills, in an application-oriented manner. Our findings also underline that institutions need to build particularly competence-based trust, e.g. strengthen their employees' abilities and motivation in supporting the job search, in order to contribute meaningfully to bridging digital divides. Our findings have further reaching implications for a whole range of Internet-based applications besides job search, not least of all e-government. As the supply of e-government services increases, policy makers may have an added incentive to ensure digital inclusion.

Our insights are also relevant for online businesses managers looking to understand and optimize user engagement on their platforms. The developed model can support them in identifying factors impeding engagement and devising targeted countermeasures. Especially

for less well-versed individuals, for example, a structured and intuitive interface as well as the offer of on-website support can be decisive for engagement. Similarly, taking measures to decrease perceived risk, such as communicating data security measures more prominently, can help to increase engagement. Our case study specifically highlights the implications for corporate human resources departments and online job search application vendors, yet our findings apply more generally to any form of data-sensitive online platform.

## **6. Limitations and future research**

This study also has some limitations. While the overall theoretical model is not limited to online job search applications but should be applicable to other settings, the case study approach may nonetheless have led to some context-specific findings. The extent of the involvement and influence of institutional social capital is likely to be particularly high for the type of Internet application studied, especially in a high social welfare state like Germany. For other types of Internet applications, other forms of capital may play a more prominent role, such as hedonic influences or economic capital. Moreover, even though we thoroughly tried to check for alternative explanations in the interviews, some behavioral observations may be attributable to unobserved factors, such as the interviewee's emotional state of mind. More research is needed to validate the applicability of our model with regard to different Internet applications, particularly in voluntary contexts, and in different countries, ideally through large-scale investigations.

Three additional avenues for future research emerge from this study. First, the impact of social capital – particularly institutional social capital – on individual engagement warrants further study. Our findings indicate that institutional social capital can play a significant role at all stages of the appraisal process yet does not have a uniformly positive influence. Scholars and policy makers stand to profit from further research on how to improve the effectiveness and acceptance of institutional measures promoting online technology use in general and e-government applications in particular.

Second, this study focuses on the appraisal phase of the coping process and only differentiates between two coping strategies, namely engagement and disengagement. Extant coping research in the field of psychology offers a large range of adaptation strategies. Some of these have been investigated within the information systems field, albeit mostly in organizational settings. The majority of consumer technology use, however, takes place in voluntary, non-organizational settings. For information systems scholars interested in strengthening the interdisciplinary

foundation of the field, developing a more fine-grained distinction of coping strategies in non-organizational settings could serve as a promising research avenue.

Finally, the field of information systems stands to profit from further research on technology skills. Extant research has catalogued and clustered types of Internet-related skills (van Deursen & van Dijk, 2011), yet little is known how this translates into specific use outcomes. Particularly content-related skills warrant further study, given their significance in influencing control within an increasingly complex online environment. A more comprehensive understanding is needed of how content-related skills are acquired and how they can be taught in order to help individuals overcome skill deficits.

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## Appendix

### Appendix A: Interview guide

<b>Table A1. Interview guide</b>	
<b>Area of inquiry</b>	<b>Key questions</b>
Respondent background	Please tell me about your professional and educational background. How old are you? Please tell me about how much you use the Internet in general. Please tell me about how long you have been searching for a job and the kind of job you are looking for.
Job search process (incident-based interviewing)	How are you going about searching for a job? What channels are you using to search for work? Have you used the Internet to search for work? If so, which Internet-based applications have you used to search for work?
Follow-up questions: Awareness	How did you learn about this application? Which other similar applications do you know? Which have you used? Which applications do you know of, but have never used?
Follow-up questions: Appraisal	What did you think about this application prior to using it? Why did you decide to use / not use this application? How do you feel about other similar applications? Why? What do you like / not like about the application that motivated you to use / not use it?
Follow-up questions: Coping, outcome, and re-appraisal	Did you use / not use the application? How did you feel about using this application? What did you think about this application after using it? What did you like / not like about using the application? Why did you decide not to use the application? What was the outcome of using the application? Would you use the application again? Why?

**Appendix B: Coding scheme and coding examples**

<b>Table B1. Coding scheme</b>	
<b>Overarching category</b>	<b>Second-order codes</b>
Awareness	Individuals which rate high on self-engagement and self-efficacy can foster creation of own awareness
	Insufficient initial awareness favors appraisal as non-opportunity
	Insufficient initial awareness limits opportunity consideration set while more awareness broadens opportunity consideration set
	Social capital can create awareness for online applications and either limit or extend the individuals consideration set
Primary appraisal	An individual's evaluation of the process of an online application influences its primary appraisal
	An individual's perceived usefulness of an online application influences its appraisal as opportunity or non-opportunity
	External contextual aspects influence the primary appraisal
	Perceived consideration set determines frame of reference for comparing and appraising of online possibilities
	Personal situation influences motivation and primary appraisal
	Primary appraisal as perceived opportunity results in engagement
	Social capital can limit or extend the set of online applications that are appraised as opportunities in the primary appraisal phase
Secondary appraisal	Cognitive dissonance: self-perceived control and denial of help despite obvious lack of control
	Content-related skills, medium-related skills and self-efficacy are a necessary requirements if applications are used for the first time
	Dissatisfaction with application interface can result in frustration/disengagement for high skill users whereas ability to control application meaningfully increases level of engagement and perceived benefit
	For "easy tasks", well-structured and well-known tasks, already medium-related skills can lead to a feeling of high control
	For more complex tasks content-related skills are required in order to experience a feeling of high control, especially in the case of low self-efficacy medium-related skills are not sufficient
	Perceived complexity fosters disengagement, in particular for low cultural capital individuals
	Self-efficacy and medium/content-related skills enable high control and engagement
	Sufficient content-related skills are necessary to navigate the multiple opportunities of online job search - a lack of these skills leads to a feeling of confusion/overload, low control (being lost), dissatisfaction and disengagement
	Sufficient medium-related skills or a high level of self-efficacy and resilience are necessary to experience a feeling of high control especially in order to tackle drawbacks of online features - not being able to do so leads to disengagement
Coping, outcome, and re-appraisal	Engagement with beneficial outcomes leads to a positive re-appraisal which reinforces behavioral patterns
	Engagement with perceived non-beneficial outcomes leads to frustration and a negative re-appraisal
	Social capital can influence the re-appraisal of online job search applications and motivate people to engage
	When evaluating the perceived benefits of online applications users compare them to each other

<b>Overarching category</b>	<b>Second-order codes</b>
Perceived risk	In case of perceived reliability risk an application is appraised as non-opportunity
	Perceived authenticity risk can lead to an appraisal as non-opportunity
	Perceived personal data security risk can lead to an appraisal as non-opportunity
Social capital and control	High control individuals do not need and do not seek help for their job search from social capital - while low control individuals wish for more exchange about the topic
	Individuals rely on and expect help from social capital institutions
	Individuals wish for more help from social capital (institutions) - especially those with low control of the job search situation/application feel lost and become disengaged if they don't get it
	Social capital can change a feeling of low control to a feeling of high control for low cultural capital individuals
	Social capital can foster engagement by facilitating processes and taking over medium-related skill tasks, however this might disable individuals from learning these skills and might eventually lead to a level of low control
	Support from social capital is evaluated to be most effective at the beginning of job search/ unemployment
	To experience a feeling of high control in a situation of low cultural capital social capital needs to be (theoretically) accessible - especially in the case of low skills and low self-efficacy
Social capital and trust	People do not feel properly prepared for online job search by educational institutions
	People evaluate social capital and this evaluation influences to which degree to which they are receptive for impulses coming from that source
	People use their (offline) social connections to find jobs
	Perceived appreciation by a social capital institution impacts the degree to which an individual trusts this institution
	Perceived authenticity and sincerity of social capital institutions important for an individual in order to build trust
	Perceived competence of social capital institutions influences the degree to which individuals trust this institution
	Perceived image of social capital institution impacts an individual's trust in that institution
	Perceived pressure enforced by social capital institution impacts the degree to which individuals trust or feel intimidated by this institution
	Perceived reliability and expectation to get help from social capital influences the degree to which an individual trusts this social capital

**Table B2. Coding examples**

<b>Second- and first-order codes</b>	<b>Representative quotations</b>
Overarching category: Secondary Appraisal	
<i>SO1. For more complex tasks content-related skills are required in order to experience a feeling of high control, especially in the case of low self-efficacy medium-related skills are not sufficient</i>	
FO1. If it is unclear how to obtain a good result the individual feels a level of low control	1.1. I don't know whether I would use an application such as Xing because I have no idea whether people on there are interested in social work and if social workers are even using it 1.2. If I were to use (the application), I would have to catch up first because I don't know how it works exactly. I imagine that would be difficult. 1.3. I wouldn't even know where to start in building my own profile, so I don't bother...
FO2. For individuals with low self-efficacy, medium-related skills can not compensate for insufficient content-related skills (and vice versa)	2.1. If I wanted to create a professional profile and used a service such as Xing, there are probably templates one can use – I feel confident that that's something I could manage even though I don't exactly know how it works. 2.2. To do that all by myself and to create a profile on my own – I mean I don't know who would look at it – but I'm not sure I would manage.
<i>SO2. Dissatisfaction with application interface can result in frustration/disengagement for high skill users whereas ability to control application meaningfully increases level of engagement and perceived benefit</i>	
FO3. Dissatisfaction with application interface can result in frustration and disengagement for high skill users	3.1. Rather than navigating through the menu of the GFEA portal, which is really frustrating, I prefer to use Google to find what I am looking for, for example the sublink to the job site. 3.2. You find a ton of information, but their website is structured exactly like my university website – in such an impractical way that I would never use it to search for something

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# Second-order digital inequality: A clickstream analysis of e-commerce use

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## **Abstract**

“Second-order digital inequality” describes a phenomenon in which certain individuals profit less from digital opportunities not only due to limited access but also due to a limited ability to use information and communication technologies (ICT). In particular, this study extends research on second-order digital inequality to the realm of e-commerce. We introduce a novel perspective on effective – potentially economically beneficial – e-commerce use that encompasses two dimensions: (1) the diversity of e-commerce platforms used by an individual and (2) the degree to which an individual uses supporting e-commerce features, such as price comparison or coupon sites. Building on technology acceptance theory and social psychology, we argue that socio-economically disadvantaged individuals are less likely than their socio-economically advantaged peers to use e-commerce in a manner that potentially promises economic gains. We empirically test our hypotheses using clickstream data that track the online behavior of 2819 US e-commerce users for six months. Our findings reveal that despite equal access, the socio-economically advantaged use e-commerce more effectively in both dimensions. Implications for research and practice are discussed.

**Keywords:** Digital inequality, e-commerce, digital divide, e-commerce platforms, e-commerce functionalities, technology acceptance, clickstream

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## **1. Introduction**

Since its inception, scholars have discussed the impact on society of information and communication technology (ICT) in general and the Internet in particular (DiMaggio, Hargittai, Neuman, & Robinson, 2001). Proponents of the Internet have argued that it could provide people with access to new ways of creating value and thus foster societal wealth and wellbeing (Hargittai, 1999; Madon, 2000). Some of these authors have even suggested that new Internet-based technologies would level the playing field between societal strata and reduce social inequality (Anderson, Bikson, Law, & Mitchell, 1995). In contrast, opponents of the Internet have contended that rather than reducing economic disparities within and across societies, the Internet could in fact lead to “increasing inequalities, improving the prospects of those who are already in privileged positions while denying opportunities for advancement to the underprivileged” (Hargittai, 2003, p. 822).

Within the debate on the social ramifications of the Internet, the phenomenon of “digital inequality” has received substantial attention (Hargittai & Hinnant, 2008; Hsieh et al., 2008; Kvasny & Keil, 2006; Riggins & Dewan, 2005). Digital inequality refers to the difference between individuals regarding their access to and ability to use Internet-based ICT (DiMaggio et al., 2004). Early studies in this domain have observed so-called “first-order” digital inequality by showing that socio-economically disadvantaged individuals typically have less access to ICT than better situated individuals (DiMaggio et al., 2001; Katz & Rice, 2002). More recently, scholars have increasingly turned their attention to “second-order” digital inequality by noting that individuals also differ with regard to how they *use* ICT depending on their socio-economic status (DiMaggio & Hargittai, 2001). Scholars have explored the manifestations and implications of digital inequality across multiple domains, focusing on central and potentially beneficial Internet applications such as information search (van Deursen, 2012), e-government participation (Belanger & Carter, 2009) and capital-enhancing websites (Zillien & Hargittai, 2009). The observations suggest that, as a result of digital inequality, socio-economically disadvantaged individuals are less able to profit from the opportunities the Internet has to offer, including better education, better access to information, and cheaper communication (Mossberger et al., 2003).

Recently, electronic commerce (e-commerce) has emerged as an additional area of opportunity creation within the digital inequality discussion. With worldwide e-commerce sales exceeding US\$1 trillion (eMarketer, 2013), e-commerce captures a substantial share of global business.

More importantly, a wide range of e-commerce platform formats and features have evolved that help individuals to optimize the economic outcome of their purchases. For example, auctions, price comparisons, daily deals, and e-coupons are means by which individuals can shop more inexpensively than in the brick-and-mortar world. In other words, users who are able to shop more effectively by leveraging e-commerce functionalities can potentially generate a substantial economic surplus (Riggins & Dewan, 2005). Thus, e-commerce might be particularly beneficial for socio-economically disadvantaged individuals.

Despite the potential benefits of e-commerce for individual – particularly underprivileged – shoppers, almost no scholarly attention has to date been devoted to digital inequality in the context of e-commerce. Prior research (Akhter, 2003; Howard, Rainie, & Jones, 2001; Zillien & Hargittai, 2009) suggests that, contrary to the homo-economicus expectations, those individuals with the least economic resources are also the least likely to fully leverage the breadth of opportunities available to realize savings when shopping online. As such, these findings imply that economic inequality in the “offline” world might be further perpetuated in the “online” universe. However, existing digital inequality research has mainly focused on selective aspects of e-commerce. In fact, so far there is only limited empirical evidence on the existence of digital inequality within e-commerce and only a limited theoretical conceptualization of what actually constitutes inequality with regard to e-commerce use. In this vein, scholars have called out for research that better conceptualizes and studies digital inequality in the context of e-commerce (Riggins & Dewan, 2005).

In this paper, we address this research gap by exploring the variation among individuals in how they use e-commerce as a function of their socio-economic status in order to determine whether digital inequality can be observed in the e-commerce realm. We focus specifically on the influence of an individual’s socio-economic status on two aspects of the online shopping process that promise economic gains, namely, (1) the extent to which an individual is able to leverage *the diversity of e-commerce platforms* available within the product purchasing step (e.g., general retailers, daily deals, flash sales) and (2) the degree to which an individual employs *supporting e-commerce features* such as e-coupons and price comparisons within the information search step to further benefit from e-commerce. We draw on technology acceptance theory and social psychology to hypothesize that socio-economically disadvantaged online shoppers tend to shop less diversely and will be less likely to make use of supporting e-commerce features. We test these hypotheses on a unique set of clickstream data that track the online behavior of 2819 US participants for six months in 2012.

Our study makes several key contributions. Most importantly, we contribute to digital inequality research (DiMaggio et al., 2004; Zillien & Hargittai, 2009) by highlighting that second-order digital inequality persists within the context of e-commerce and that contrary to what one would expect, socio-economic status does not primarily impact *how much* individuals buy online, but rather *how* they search for and buy products. We further add to the broader context of information systems research by introducing clickstream data as the empirical basis of our research, which represents an innovative approach to investigating technology acceptance based on actual rather than self-reported, intended behavior. Moreover, we introduce a novel perspective on potentially beneficial e-commerce system use from an economic point of view. Finally, our research has important implications for public policy and managerial practice. Understanding how socio-economic status impacts e-commerce use may influence policy making with regard to digital skills, ICT education and consumer protection. Our insights may also help business practitioners to effectively target different societal groups.

## **2. Theory and hypotheses**

### **2.1 Digital inequality: The perpetuation of socio-economic status online**

“Digital inequality” denotes the difference between individuals in terms of their access to and ability to use ICT, which in turn restrains certain individuals from realizing the opportunities offered through these technologies (DiMaggio et al., 2004). While digital inequality has been observed with regard to various demographic dimensions such as gender, race, and age (Chaudhuri, Flamm, & Horrigan, 2005; Rice & Katz, 2003), the phenomenon has been particularly highlighted in the context of socio-economic differences between individuals as reflected in their income and education (Jung, Qui, & Kim, 2001). Mossberger et al. (2003), for instance, suggest that individuals with lower income and education levels are restricted in their job prospects due to their relative lack of access to ICT and the associated skills in a work environment. Relatedly, Hsieh et al. (2008) show that individuals with fewer financial resources show less intention to use a government-funded TV Internet connection.

Digital inequality constitutes a complex and multi-faceted societal challenge at a global level as well as within national societies (OECD, 2013; UN, 2013). Researchers have argued that digital inequality is a perpetuation and a reinforcement of underlying social disparities in the “real” world (Kvasny & Keil, 2006; see also Norris, 2001; Warschauer, 2003). It has been suggested that, comparable to the so-called “Matthew effect” (Merton, 1973), peoples’ initial

advantages in technology access may translate into increasing relative returns over time, thereby further widening the gap between the more and the less privileged parts of society.

Scholars have devoted increasing attention to digital inequality and its underlying mechanisms. Earlier research in this domain focus on the first-level “digital divide”<sup>25</sup> (DiMaggio & Hargittai, 2001), which denotes differences in people’s access to ICT and its sociological implications such as exclusion from online education (Katz & Rice, 2002). More recent studies note that access to the Internet is losing importance, with broadband penetration in developed countries almost at saturation levels (e.g., in 2012, 80% of individuals had access to broadband in the US; OECD, 2013). Correspondingly, recent research seeks to elucidate so-called “second-level”<sup>26</sup> digital inequality (Hargittai, 2002): rather than studying *whether* individuals have access to the Internet or not, the debate now focuses on exploring differences in *how* people use the Internet to create opportunities for themselves. Mossberger et al. (2003), in particular, suggest three different manifestations of digital inequality in addition to disparities in access to ICT: first, a skills divide related to the individual ability to handle computers and the Internet and to obtain access to information via these devices; second, an economic opportunity divide resulting from people’s inability to participate in Internet-based education, training, and employment opportunities; and third, a democratic divide due to the inability to engage in e-government. In this vein, digital inequality scholars have explored aspects such as general Internet skills (Hargittai, 2010; Litt, 2013) and the adoption of e-government (Belanger & Carter, 2009; Helbig, Ferro, & Boella, 2009). For instance, van Deursen and van Dijk (2011) study Internet skills in the Dutch population and observed that a lower educational level predicted lower Internet skills. In our study, we focus on one additional principal Internet-based application that has been proposed to be affected by and to affect digital inequality (Riggins & Dewan, 2005): the use of electronic commerce.

## **2.2 E-commerce and the potential economic benefits of platform use diversity and supporting e-commerce features**

E-commerce in the business-to-consumer context is defined as the trade of products and services online (Olson & Olson, 2000). The U.S. Department of Commerce (2014) estimates

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<sup>25</sup> DiMaggio and Hargittai (2001) differentiate between the “digital divide” – used to connote whether an individual has or does not have access to a technology – and “digital inequality”, which refers not just to differences in access but also to differences in how individuals with formal access to a technology use it. The term “digital inequality” has dominated the research debate over the last decade as increasing ICT penetration has diminished the purely access-driven divide.

<sup>26</sup> The terms “first-level” and “second-level” were originally used to define digital divide and digital inequality, respectively. Within current research, these terms are used interchangeably with “first-order” and “second-order”.

that in 2013, US citizens spent US\$ 263 billion online for products and services and that online sales will reach US\$ 370 billion by 2017 (Forrester Research Inc, 2013). In 2014 alone, e-commerce sales were expected to increase by an additional 14% compared to 2013 (Centre for Retail Research, 2014).

Given the growing importance of e-commerce, scholars in information science have studied various aspects of people's e-commerce use. For instance, behavioral research in e-commerce illuminates the factors that motivate individuals to engage in online shopping (Gefen, Karahanna, & Straub, 2003; Gefen & Straub, 2000; Pavlou & Fygenon, 2006). Overby and Lee (2006) find that utilitarian aspects such as convenience and the ability to save time and money are key factors driving e-commerce use. Other researchers have investigated specific e-commerce functions such as auctions and e-coupons. Jung and Lee (2010), for instance, find that the redemption rate for online coupons is significantly higher than that for offline coupons.

In the context of second-order digital inequality, it is important to define what actually constitutes effective – that is, potentially beneficial from an economic point of view – e-commerce use to be able to identify meaningful differences in the way *how* individuals shop online. This necessitates a more holistic perspective on e-commerce use that goes beyond simply measuring use or non-use as a binary variable. Burton-Jones and Grange (2012, p. 633) propose a definition of effective use as “using a system in a way that increases achievement of the goals for using the system.” Given the premise of utility-maximizing decision making, online shoppers will aim to realize a successful product or service transaction at the minimum economic and opportunity cost. Building on this premise and in line with Alvesson and Kärreman (2007), we adopt a view of “sensitive constructions” (p. 1269) to develop a new perspective on e-commerce use by involving a flexible theoretical framework and taking a “reflexive approach to empirical material” (p.1269), that is, considering alternative framings and constructions conveyed by the empirical material.

Buyer decision-making models break down the purchasing process into a number of steps<sup>27</sup> (Engel, Kollat, & Blackwell, 1973), of which information search and the product purchasing decision are considered to be the most important within the online context (Gefen & Straub, 2000; Pavlou & Fygenon, 2006). In the information search step, consumers can choose

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<sup>27</sup> The Engel, Kollat and Blackwell model comprises five steps: problem/need recognition, information search, evaluation of alternatives, purchase, post-purchase evaluation (Engel et al., 1973). Alternative comprehensive consumer decision making models put forward by Nicosia (1966) and Howard and Sheth (1969) follow a similar approach.

between different e-commerce features to optimize prices (in addition to obtaining general product information), predominantly through price comparisons and e-coupons<sup>28</sup>. When considering the product purchasing step, the continuous evolution of the e-commerce landscape over the last decade needs to be taken into account. Today, consumers can choose among a diverse variety of formats and vendors from which to buy a product. For instance, the rapid proliferation of innovative formats such as auction, daily deal or flash sale sites provide consumers with an increasing range of alternatives to traditional online retailers such as Amazon.com and the opportunity to save money by finding the best deal. Table 1 provides a summary of the different e-commerce platforms and their potential consumer value. Consequently, a conceptualization of effective e-commerce use should account for the heterogeneous information search and product purchase options available that offer individuals the potential to achieve economic benefits and thus go beyond the traditional use concept of a simple transaction made online.

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<sup>28</sup> Online reviews of retailers are also an important e-commerce feature and serve as a signaling function for consumers to make inferences about price validity (Bodur et al., 2015). As such, they may influence the choice of retailer, however they do not substitute the use of price comparison or e-coupon sites as a means to optimize purchase prices.

<b>Table 1. E-commerce platforms and potential consumer value add</b>				
Purchasing process step	E-commerce platform	References	Definition	Examples of potential consumer value add
Information search	Price comparisons	Bock, Lee, & Li (2007); Bodur, Klein, & Arora (2015); Grewal, Monroe, & Krishnan (1998); Passyn, Diriker, & Settle (2013); Tan, Goh, & Teo (2010)	Website with a search engine that aggregates product listings from different retailers.	Substantial price dispersion exists online (Lindsey-Mullikin & Grewal, 2006). Price comparisons can generate value through price transparency and arbitrage (Bock et al., 2007).
	E-coupons	Chiou-Wei & Inman (2008); Jung & Lee (2010); Oliver & Shor (2003); Venkatesan & Farris (2012)	Website that aggregates free promotional savings codes that can be applied to a purchase transaction on another e-commerce website.	In 2014, consumers in the US made total savings of \$3.6 billion on consumer packaged goods by redeeming coupons (NCH Marketing Services, 2015).
Product purchase	General retailer	Campbell, Wells, & Valacich (2013); Gefen et al. (2003); Hinz, Hann, & Spann (2011); Luo, Ba, & Zhang (2012); Overby & Lee (2006); Pavlou & Fygenson (2006)	Website offering a wide range of products not limited to one brand or product type.	Value for money, convenience of locating and comparing multiple vendors, and time savings relative to offline alternatives (Overby & Lee, 2006). Low search and switching costs online facilitate cross-shopping across multiple websites and platforms (Pathak, 2012).
	Specialized retailer		Website specialized in one type of product with multiple brands on offer.	
	Brand shop		Website offering a range of products dedicated to one brand.	
	Auctions	Chang & Chen (2015); Dholakia & Simonson (2005); Suter & Hardesty (2005)	Website with a wide range of products not limited to one brand or product. Purchase via bidding process or direct purchase at fixed price.	Consumers extract a median surplus of at least \$4 per eBay auction (Bapna, Jank, & Shmueli, 2008).
	Daily deals	Boon (2013); Gafni, Geri, & Aziz (2014); Hughes & Beukes (2012)	Website offering virtual vouchers for a limited time for a selection of typically local, discounted goods/services which may be employed offline.	According to Groupon's own statistics, it has sold more than a million deals and saved consumers \$42 million (Grewal et al., 2011).
	Flash sales	Barone & Roy (2010); Martinez & Kim (2012); Ryu & Feick (2007)	Website offering a limited stock of discounted (often brand-name) products. Purchase directly on the website at a fixed price.	Mostly sign-up only, exclusive promotions of limited stock at sharp discounts (often 50% or more) (Grewal et al., 2011).

In this study, we focus on two specific aspects of e-commerce use, both of which are particularly likely to create economic benefits for users in either the information search or the product purchasing phase: (1) the extent to which an individual is able to leverage the diversity of e-commerce platforms available within the product purchasing step (e.g., general retailers, daily deals, flash sales) and (2) the degree to which an individual employs supporting e-commerce features such as e-coupons and price comparisons within the information search step to further benefit from e-commerce. Figure 1 summarizes the key aspects of our proposed conceptualization of e-commerce use.

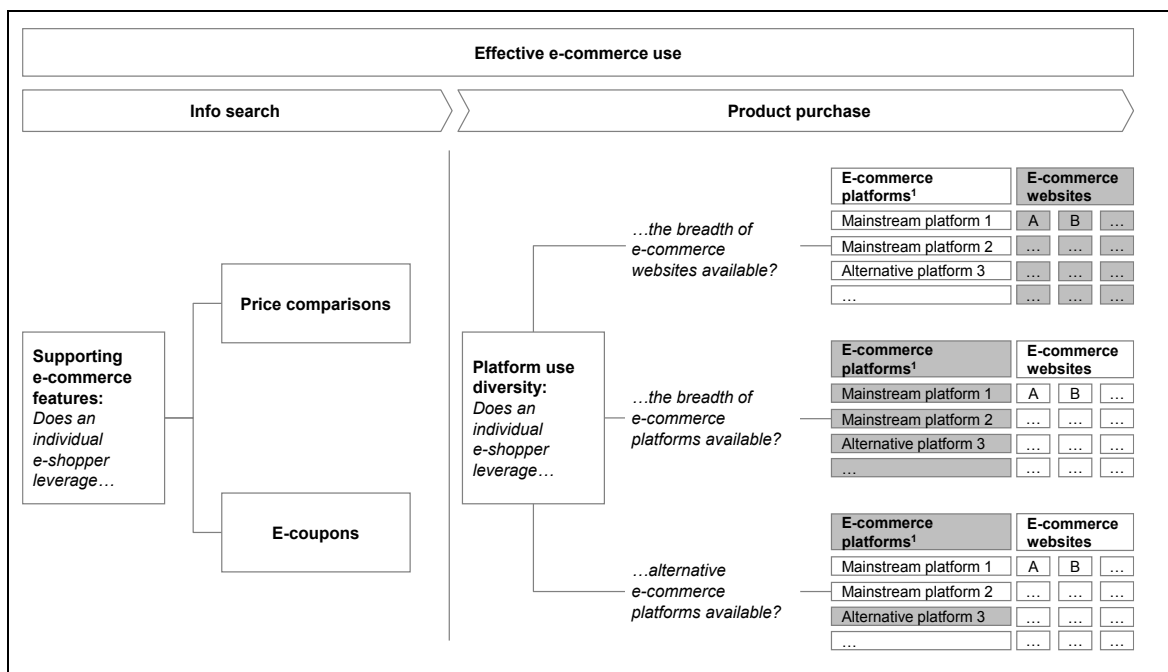


Figure 1. Dimensions of effective e-commerce use at the focus of the study

We define “e-commerce platform use diversity” as the variety of e-commerce platforms an individual uses when shopping online. This definition entails two particular aspects. First, it accounts for the general degree to which an individual makes use of different e-commerce websites and different e-commerce platforms when shopping online. Online shoppers can access a wide a range of e-commerce platforms: for example, general retailers such as Amazon.com, specialized retailers such as Zappos.com, and brand shops such as Nike.com. Research within offline retail has shown that a larger number and variety of store visits per week leads to an economic advantage (Carlson & Gieseke, 1983): those individuals shopping for groceries who make more trips to different stores achieve lower prices on average because of price dispersion between stores. Similar patterns of price dispersion can be observed in the online space (Ba, Stallaert, & Zhang, 2012), while information search and switching costs are



significantly lower (Carter, Wright, Thatcher, & Klein, 2014). Correspondingly, online shoppers who are able to selectively switch between different e-commerce websites and platform formats, and thereby leverage the breadth of product offerings available are more likely to achieve economic gains.

A second particular aspect entailed in the definition of platform use diversity is the users' participation in 'alternative' e-commerce formats such as auctions (e.g., Ebay.com), flash sales (e.g., Gilt.com), and daily deal sites (e.g., Groupon.com). Prior research shows that alternative e-commerce formats in particular offer significant cost savings for users. For instance, Bapna et al. (2008) estimate that the consumer surplus from auctions on Ebay.com exceeded US\$ 7 billion in 2003. Similarly, daily deal and flash sale websites offer heavily discounted deals for a limited time (Boon, 2013; Martinez & Kim, 2012), improving users' odds of achieving lower prices than they could through other sales channels.

We define "*supporting e-commerce features use*" as an individual's use of price comparisons and e-coupons in connection with an online transaction. Price comparison websites such as Shopping.com, Bizrate.com, and Nextag.com increase consumer power (Rezabakhsh, Bornemann, Hansen, & Schrade, 2006) by creating price transparency and by offering additional product relevant information. E-commerce research has shown that the potential savings resulting from the use of price comparison websites can be significant. For instance, Baye, Morgan, and Scholten (2004) examine four million prices for 1000 consumer electronics products and find that despite increased transparency, price dispersion ranged from an average of 3.5% up to 23%.

Moreover, consumers can achieve additional savings by leveraging websites that offer free promotional e-coupons such as Retailmenot.com or Coupons.com. E-coupons are digital codes that entail a price reduction for a given product or website (Jung & Lee, 2010). Thus, using supporting e-commerce features enables users to capture a higher economic surplus per transaction on a given platform. The use of price comparisons and e-coupons in combination can be expected to elicit an even higher consumer surplus.

## **2.3 Digital inequality in e-commerce use**

### ***3.3.1 E-commerce use and the technology acceptance model***

Extant studies have repeatedly called for research on digital inequality in the context of different ICT use applications (DiMaggio et al., 2004, 2001; Hargittai & Hinnant, 2008; Zillien

& Hargittai, 2009) and of e-commerce in particular (Akhter, 2003; Hoffman, Novak, & Schlosser, 2006). Specifically, Riggins and Dewan (2005) introduce the notion of an “e-commerce divide,” which they defined as “certain people’s inability to make use of more advanced e-commerce online functionalities and services” (2005, p. 318). They argue that even in the case of equal Internet access, socio-economically disadvantaged individuals might be less able to seize the multiple opportunities to achieve the economic gains that are offered by e-commerce.

The notion of an “e-commerce divide” carries a number of intriguing theoretical implications. Most strikingly, such a divide contradicts assumptions about rational behavior, opportunity cost and the decreasing marginal value of money. Under such assumptions, one would expect that the motivation to minimize costs through e-commerce be strongest for those individuals with the least financial resources and that those who earn the least would incur lower opportunity costs when investing time online. Ultimately, these two factors would prevent the emergence of an e-commerce divide. Moreover, the existence of an e-commerce divide appears to be counterintuitive because e-commerce theoretically carries the potential to reduce – rather than reinforce – disparities regarding consumption possibilities in the offline world (Anderson et al., 1995). While in the brick-and-mortar universe, product availability, access, and pricing are highly dependent on the consumer’s place of residence and typically favor those consumers who live in well developed areas, in the online world, the product offering and prices are identical for everyone. In addition, the costs to search for products and prices on the Internet are lower compared to the costs in the offline world due to, for instance, automated price comparisons. In the offline world, information search is costly, which might prevent those in lower income classes from extensively searching for the best product at the best price. Altogether, the notion of an “e-commerce divide” contradicts homo-economicus assumptions about consumer behavior and the theoretical “equalizing power” of e-commerce. Thus, it seems particularly interesting to explore if and why digital inequality can be observed in the field of e-commerce.

To build hypotheses on the relation between an individual’s socio-economic status and his or her tendency to use a diverse set of e-commerce platforms and supporting e-commerce features, we draw on Davis’ (1989) technology acceptance model (TAM). TAM is a particularly suitable theoretical lens for the context of our study since is a widely accepted model in information systems research (Venkatesh & Bala, 2008; Venkatesh et al., 2003, 2012), it has proven to yield

rich insights in the context of digital inequality (Hsieh et al., 2008), and has been extended to robustly predict various facets of consumer usage behavior in the context of e-commerce (Gefen & Straub, 2000; Koufaris, 2002; Pavlou, 2003), such as online auctions (Stern, Royne, Stafford, & Bienstock, 2008) and e-coupons (Kang, Han, Fortin, Hyun, & Eom, 2006). TAM originally predicts an individual's intention to use new technologies as a function of two factors (Davis, 1989): perceived ease of use, which describes the subjective degree of effort required to use a technology; and perceived usefulness, which refers to the individual's perception of the utilitarian gains that can be derived from using a technology. In our study, we use the equivalent term of utilitarian motivation in lieu of perceived usefulness (see Hsieh et al., 2008) to denote an individual's motivational disposition.

In line with prior e-commerce research (e.g., Ahn, Ryu, & Han, 2007; Pavlou, 2003), we apply an extended, context-specific TAM. In their quest to continuously refine the TAM and adapt it to the context of e-commerce, scholars have dedicated particular attention to perceived risk as an additional precursor of an individual's e-commerce usage (Gefen et al., 2008). The individual's perception of risk<sup>29</sup> is a quintessential component of e-commerce use because the consumer and the Internet store are physically separated, and online transactions therefore have an inherently impersonal nature (Bhatnagar & Ghose, 2004; Kim & Benbasat, 2003; Pavlou, 2003). Glover and Benbasat (2010) describe the perceived risk of online shopping as an aggregate of an individual's subjective assessment of three dimension of risk: first, the risk of information misuse, for example the abuse of personal or financial data; second, the risk related to product benefits, for instance that a product will not arrive or might be defective; and third, the risk of functionality inefficiency, for example that returning a product will be too difficult.

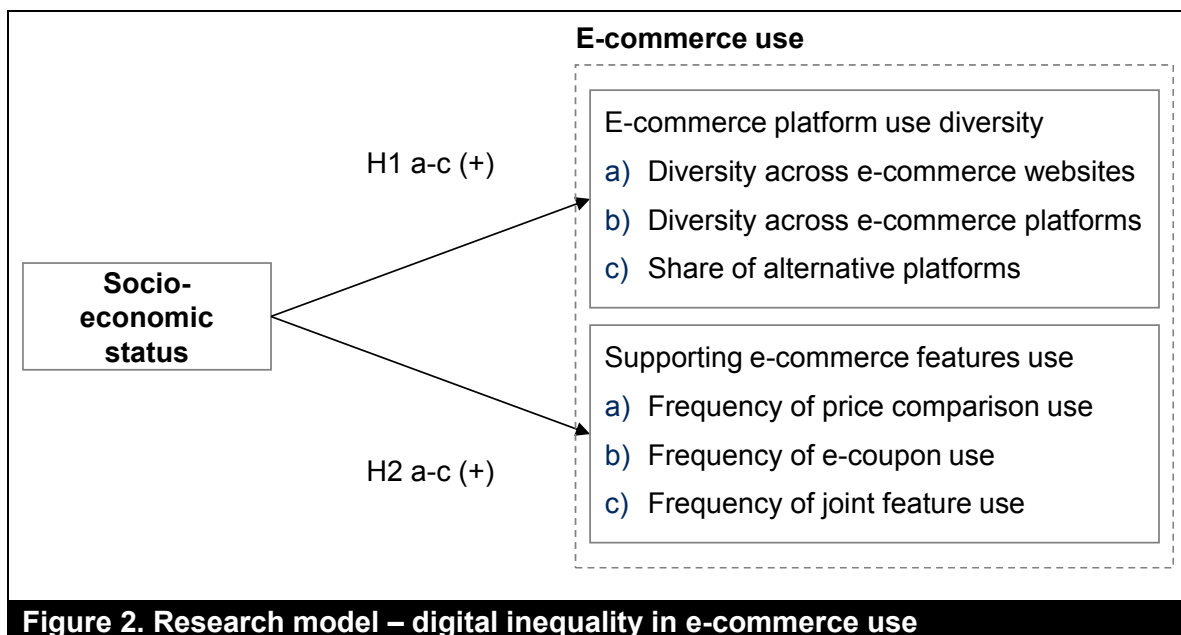
Further, scholars have introduced the construct of hedonic motivation as a complementary element to increase the predictive power of the TAM model in the context of e-commerce (Ahn et al., 2007; Ha & Stoel, 2009; van der Heijden, 2004). In this context, hedonic motivation is the degree to which an individual can derive enjoyment from online shopping (Childers, Carr, Peck, & Carson, 2001). In contrast to utilitarian motivation, which describes the outcome-driven extrinsic motivational factors for using a technology, hedonic motivation refers to the intrinsic motivation reinforced only by "the process of performing the activity per se" (Davis

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<sup>29</sup> In line with Glover and Benbasat (2010), we focus on the construct of perceived risk rather than the closely related construct of trust given that a reduced level of perceived risk will require a lower level of necessary trust in the first place. Trust itself has been researched in great detail as well and discussed as an antecedent of perceived usefulness, perceived ease of use and perceived risk (Pavlou, 2003).

et al., 1992). Researchers investigating online consumer behavior have shown that hedonic aspects of online shopping are different from those in the brick-and-mortar universe but equally important. For instance, sensory stimulation offered through a website, the playfulness of a website, and the ability to share e-commerce experiences with others improve the odds that consumers perceive online shopping to be enjoyable and show more intention to shop online (e.g., Ahn et al., 2007; Childers et al., 2001; Lin, Wu, & Tsai, 2005; Moon & Kim, 2001).

The central idea of our study is that because of their socio-economic status, individuals tend to differ in their use of e-commerce. The socio-economically disadvantaged will differ from their advantaged peers in terms of their perceived ease of use, that is, the degree to which they are affected by e-commerce complexity. Moreover, less privileged individuals are likely to differ from the more privileged in their motivational dispositions, that is, regarding the relative importance of hedonic and utilitarian stimuli. Lastly, they are likely to be distinct regarding the degree to which they perceive e-commerce to be risky. We argue that these dispositions, in turn, lead to status-induced differences in how individuals behave regarding their e-commerce platform use diversity and their use of supporting e-commerce features. Table 2 in the next chapter illustrates the general logic of our theorizing by using TAM constructs to link socio-economic status and e-commerce use. We display our research model in Figure 2 and describe it in the following passages.



**Figure 2. Research model – digital inequality in e-commerce use**

### ***3.3.2 Digital inequality in e-commerce platform use diversity***

Three rationales lead us to argue that socio-economic status is linked to platform use diversity. First, the complexity of using multiple e-commerce platforms is likely to be affected by the individual's perceived ease of use. Technology complexity has long been identified as a major barrier to ICT use, including e-commerce (Rice & Katz, 2003). However, social psychology suggests that socio-economic differences cause people to vary in how they perceive complexity: privileged individuals typically have better access to skills and techniques that allow them to cope more easily and flexibly with challenges (Fan & Eaton, 2001), which is one reason why they are less affected by stress-creating factors (Hoffman, 2003), including environmental complexity. Relatedly, scholars studying individual digital skills found a divide between socio-economic classes regarding the skills required to accomplish certain Internet tasks. For instance, van Deursen (2012) observes that individuals with a lower level of education were less able to access health information on the Internet. In this vein, we argue that the perceived ease of using a diverse set of e-commerce platforms is likely to be higher for the socio-economically advantaged given their general disposition to cope more easily with complexity as well as their higher level of education and Internet skills. Therefore, we anticipate that the socio-economically advantaged are likely to shop more diverse than the socio-economically disadvantaged.

Second, socio-economic status is likely to influence the motivational dispositions of individuals (Holbrook & Hirschman 1982; Holbrook 1986), in particular, their utilitarian and hedonic motivations. Findings from digital inequality research suggest that obtaining utilitarian benefits is likely to be relatively more important for the socio-economically advantaged as opposed to their disadvantaged peers. For instance, Hargittai and Hinnant (2008) investigated the Internet use behavior of young adults and found that those with less education and from lower income backgrounds used the web to a lesser degree to read news or to gather information on finance, health, politics or products. Further, Bonfadelli (2002) studies the Internet use behavior of more than 1400 individuals and found that those with less formal education used the Internet mostly for entertainment, while those study participants with more education used the Internet instead for informational and serviced-related purposes. Some scholars argue that the better education of the socio-economically advantaged puts them in a better position to assess and acknowledge the usefulness of ICT functionalities (Norris, 2001). Other authors see the relatively lower importance of utilitarian benefits as a consequence of the lack of digital

skills required to fully leverage existing utility-maximizing opportunities (van Deursen & van Dijk, 2011).

A high level of utilitarian motivation, in turn, positively influences an individual's inclination to shop using a diverse range of e-commerce platforms. Shopping on different platforms provides utilitarian benefits, such as a greater potential to save costs and to profit from better product availability as a result of visiting a range of shopping platforms instead of just one. Similarly, the use of alternative platforms such as auctions, daily deals and flash sales offers significant cost savings (Bapna et al., 2008; Boon, 2013; Martinez & Kim, 2012) and thus provides utilitarian benefits. Given the relatively higher importance of utilitarian benefits for the socio-economically advantaged, they will most likely exhibit more diverse shopping patterns than socio-economically disadvantaged individuals.

Vice-versa, consumer research and social psychology suggest that obtaining hedonic benefits is likely to be relatively more important to the socio-economically disadvantaged than to their more advantaged peers. Less privileged individuals were found to be generally more exposed to stressors (Aneshensel, 1992) and hence more in need of hedonically achieved stress relief, which is, for instance, provided by shopping (Arnold & Reynolds, 2003). Moreover, socio-economically disadvantaged individuals exhibit a greater tendency to cope with life difficulties by escaping into different worlds (Parker & Endler, 1996). This form of social escapism has already been found to be a hedonic motivational driver of online shopping behavior (Kim, 2002; Monsuwé, Dellaert, & Ruyter, 2004; Overby & Lee, 2006). Internet-based entertainment provides a further opportunity especially for the socio-economically disadvantaged to "get away from it all" (Mathwick, Malhotra, & Rigdon, 2001). As such, it is not surprising that earlier work on digital inequality finds that socio-economically disadvantaged individuals are more strongly attracted to the hedonic elements of ICT use than their more advantaged peers (Hsieh et al., 2008).

<b>Table 2. Using TAM constructs to link socio-economic status and e-commerce use</b>					
<b>TAM construct</b>	<b>Definition</b>	<b>Relative importance of construct depending on socio-economic status</b>	<b>Support for identified relative importance from existing literature</b>	<b>Illustration of specific TAM construct influence on e-commerce use (examples)</b>	
				<b>Platform use diversity</b>	<b>Supporting e-commerce features</b>
<b>Perceived ease of use (PEOU)</b>	Subjective degree of effort required to shop online (Davis, 1989)	Relatively <b>higher</b> for the <b>socio-economically advantaged</b>	Fan & Eaton (2001); Hoffman (2003); Rice & Katz (2003); Van Deursen (2012)	(+) Requires PEOU to manage, for example the complexity of multiple interfaces	(+) Requires PEOU, for example to evaluate price comparison search results
<b>Utilitarian motivation</b>	Individual perception of gains that can be derived from shopping online (Davis, 1989)	Relatively <b>higher</b> for the <b>socio-economically advantaged</b>	Bonfadelli (2002; Hargittai & Hinnant (2008); Norris (2001); van Deursen & van Dijk (2011)	(+) Provides utilitarian benefit of cost savings, for example through using auctions or daily deals	(+) Provides utilitarian benefit of cost savings, for example through price transparency
<b>Hedonic motivation</b>	Degree to which an individual can derive enjoyment from online shopping (Childers et al., 2001)	Relatively <b>higher</b> for the <b>socio-economically disadvantaged</b>	Aneshensel (1992); Hsieh et al. (2008); Mathwick, Malhotra, & Rigdon (2001); Parker & Endler (1996)	(+) Provides hedonic benefits such as novelty, experiencing thrills and feeling of escaping reality	(+) Hedonic benefits limited, for example to the joy of searching
<b>Perceived Risk</b>	Individual assessment of the risks associated with online shopping related to information misuse, product benefits and functionality inefficiency (Glover & Benbasat, 2010)	Relatively <b>higher</b> for <b>socio-economically disadvantaged</b>	Schechter (2007); McLeod & Kessler (1990); Bhatnagar & Ghose (2004); Shaw (1996)	(-) Increases risk, for example through multiple disclosures of personal and financial data	Not applicable

Diverse online shopping patterns may also be driven by hedonic motivation. In particular, hedonic benefits such as novelty (Arnold & Reynolds, 2003), a feeling of escaping reality (Mathwick et al., 2001) or experiencing thrills in the case of auctions (Turel, Serenko, & Giles, 2011) may be further augmented through diverse e-commerce use. Consequently, from a hedonic motivation point of view, the socio-economically disadvantaged may be more inclined to shop on a broad range of platforms. However, we believe that hedonic motivators are less relevant in the context of our study than utilitarian motivators given that scholars found utilitarian motivation to have a much stronger impact on ICT use than hedonic motivation. Notably, this relationship has been substantiated not only in the case of workplace ICT use (Davis et al., 1992), where it might be expected, but also in the case of leisure activities such as e-commerce (e.g., Ahn et al., 2007; Childers et al., 2001). These findings reflect that people predominantly use ICT in an instrumental way to achieve a certain outcome, corresponding to a utilitarian motivation, rather than for reasons of performing the activity per se, which correspond to a hedonic motivation. So even though shopping on a broad range of platforms may convey some hedonic benefits, utilitarian benefits are expected to be a stronger driver of diverse shopping behavior. As such, socio-economically advantaged individuals, who are more strongly motivated by utilitarian benefits, will most likely exhibit more diverse shopping patterns than socio-economically disadvantaged individuals, who are more strongly motivated by hedonic shopping benefits.

Third, socio-economically disadvantaged individuals are less likely to shop on a broad range of platforms because their risk perception of a given e-commerce activity is likely to be relatively higher than that of their advantaged peers. Economists generally postulate that people with higher incomes are less risk averse (Schechter, 2007). Additionally, psychologists have found that individuals from lower income classes show more intense emotional vulnerability with regard to financial losses (McLeod & Kessler, 1990). In the specific context of e-commerce, Bhatnagar and Ghose (2004) segment consumers based on their risk and benefit perceptions of online shopping and find that the perceived product risk as well as the perceived security risk were highest in the lowest income class.

A high level of perceived risk associated with online shopping, in turn, inhibits diverse shopping behavior on multiple platforms. With the transfer of transactions from the offline to the online world, the risk associated with buying a product has undeniably risen and constitutes a major influencing factor on e-commerce behavior (Pavlou, 2003). The required multiple



disclosures of private and financial data on the different e-commerce sites associated with a diverse shopping behavior further increases the probability of personal data misuse. This might discourage risk-averse individuals from engaging in diverse e-commerce use. This behavior is likely to be reinforced as soon as an individual has built a trust-based relationship with one e-vendor through repeated transactions, making risk-averse individuals even more reluctant to switch to another e-vendor (Gefen, 2002). Given the relatively higher risk perception of online shopping of the socio-economically disadvantaged, they might thus be less inclined to shop on a broad range of platforms compared to the socio-economically advantaged.

Based on the differential behavior regarding perceived ease of use, hedonic and utilitarian motivation, and perceived risk, we formally propose the following:

*H1a-c: The higher an individual's socio-economic status, the more diverse will be that individual's transaction behavior when shopping online in terms of (a) e-commerce websites used, (b) e-commerce platforms used, and (c) share of alternative e-commerce platforms used.*

### **3.3.3 Digital inequality regarding supporting e-commerce features use**

In line with the argumentation above, perceived ease of use and differences in motivational dispositions will result in differential use of supporting e-commerce features by the socio-economically advantaged and disadvantaged. Perceived risk is assumed to not influence the use of supporting e-commerce features because price comparison and e-coupon websites do not usually require the disclosure of personal data, and the use of these features does not constitute a transaction.

Building on findings that perceived ease of use is relatively lower for the socio-economically disadvantaged, it appears likely that they will experience greater difficulty in using supporting e-commerce features. The use of supporting e-commerce features adds complexity to online shopping. While it is relatively easy for an individual to access price comparison websites, a certain level of information evaluation skills is required to sort out search results and to select a vendor, thereby imposing a potential complexity barrier (van Deursen & van Dijk, 2011). In line with traditional coupon research (Levedahl, 1988), we assume that the complexity of searching for e-coupons on a broad variety of websites and testing e-coupon validity constitutes an additional barrier. Building on the argumentation above, we argue that due to fewer skills

and a lower ability to handle complexity, using supporting e-commerce features will be more difficult for the socio-economically disadvantaged.

Given that the socio-economically disadvantaged are also likely to be relatively less motivated by utilitarian benefits, which are important drivers of supporting e-commerce feature use, they are likely to use price comparisons and e-coupons less frequently when shopping online. The use of price comparison websites and e-coupons is mainly driven by utilitarian motivation, while hedonic motivation plays a minor role. Price comparisons generate utilitarian value through increased price transparency and the potential to save costs (Bock et al., 2007). Similarly, e-coupons offer additional savings at the point of sale by providing product- or retailer-specific promotional discounts and thus primarily cater to utilitarian motivations (Jung & Lee, 2010). For both price comparisons and e-coupons, the factors related to hedonic motivation are limited. As theorized above, the socio-economically disadvantaged are relatively less motivated by utilitarian shopping benefits. Thus, we posit that the socio-economically disadvantaged will be less motivated to use supporting e-commerce features. Building on the reasoning above, we formally propose the following:

*H2a-b: The higher an individual's socio-economic status, the higher will be the frequency of (a) price comparison use and (b) e-coupon use when shopping online.*

An individual who not only uses either price comparisons or e-coupons but also uses both conjointly is likely to achieve even higher gains but at the same time will be faced with higher task complexity. Thus,

*H2c: The higher an individual's socio-economic status, the higher will be the frequency of joint price comparison and e-coupon use when shopping online.*

### **3. Methodology**

#### **3.1 Data sample**

We tested our hypotheses on a unique set of clickstream data courtesy of comScore. Clickstream data represents a record of an individual's online activities. It tracks the user's navigation path online, collecting information, for example, on the websites the user visits, on the actions conducted at each site as well as on e-commerce transaction details such as domain names, products and prices. In contrast to site-centric data, which only assimilates information for a given website, syndicated clickstream data is "user-centric" (Padmanabhan, Zheng, &

Kimbrough, 2001) because it chronicles the online activities of individual users across multiple websites.

Clickstream data provides a particularly powerful empirical basis for studying facets of Internet use. It is frequently applied in the field of online marketing to evaluate browsing behavior, the effectiveness of online advertising and online shopping patterns (Bucklin & Sismeiro, 2009). With regard to the latter, the focus of research has largely been on predicting purchase conversion, understanding the factors driving successful transactions and investigating alternative pricing mechanisms in auctions (Moe, 2006; Park & Bradlow, 2005).

Using clickstream data as an empirical basis has several key advantages. First, it avoids the typical weaknesses of cross sectional data such as self-report bias and common rater effects (Podsakoff et al., 2003) by tracking actual behavior. Second, a clickstream dataset typically covers a period of several months. The longitudinal nature of the data means that the risk of a sustained behavioral bias by the user is minimal. Third, user-centric clickstream data in particular encompasses a very large and detailed set of information that would be difficult to aggregate using survey-based measures. For the purpose of our study, which attempts to understand e-commerce use in a more in-depth and nuanced manner, clickstream data provides the level of detail needed to accurately capture actual use. These advantages come with the tradeoff that the clickstream dataset does not provide empirical insight on the mediating factors that influence use.

Our dataset comprised 19958 Internet users from 10000 households in the US whose Internet activities were tracked for a period of six months from May to October 2012. Participants were part of an opt-in comScore consumer sample which is compiled using industry standard methodologies such as random digit dial (RDD) recruitment and membership incentives (Padmanabhan et al., 2001). To normalize self-selection bias in the opt-in sample, comScore employs a technique called “iterative proportional fitting”. In this process, they use an enumeration survey and calibration panel sample with participants only recruited via offline channels (Cook & Pettit, 2009). The obtained measures are used to calculate a weighting scheme for the opt-in panel to ensure population representativeness and normalize the main sources of online recruitment bias as well as self-selection bias, such as proportionally attracting more heavy Internet users (comScore, 2014).

To ensure sample validity, we applied a number of restrictions. We limited transactional data observations to four product categories: apparel & accessories, consumer electronics, home supplies & living, and health & beauty. Other purchases, such as music downloads, digital subscriptions and food delivery orders, were excluded. The rationale behind this selection was to define a homogeneous comparison basis that only includes products that can be purchased online on several different platforms and for which price comparisons and e-coupons are available. In addition, we only included participants with complete demographic data, a minimum age of 18 years and at least one e-commerce transaction in the observation period. The resulting sub-sample encompassed 2819 users and 14260 transactions. This constitutes one of the largest samples in the study of e-commerce use to date.

The dataset included user-level browsing and transaction-related data points from the top 200<sup>30</sup> mainstream e-commerce websites in the US and the largest alternative e-commerce, e-coupon and price comparison websites. As we were interested in e-commerce platforms rather than individual websites, we classified the URLs in one of the following disjoint categories: general retailers, specialized retailers, brand shops, auctions, daily deals, flash sales, price comparisons and e-coupons. The URL classification was undertaken by two independent raters, who received the same platform descriptions and coding criteria. Intercoder reliability between the two raters was 97%. After discussing the eight discrepant codes, the two raters reached full agreement (see Appendix).

Table 3 summarizes the sample characteristics. We observe an even gender split in all except for the highest income category. The age distribution is skewed towards users between the ages of 18-44. This is, however, consistent with findings on the age distribution of the actual online shopping population in the US (Forrester Research Inc, 2013). Over 80% of the participants use the Internet for personal purposes for at least five hours a week. This reflects a good level of exposure. Notably, the average number of transactions for each income class is fairly equal across groups, and participants from the lowest income class spend a proportionally higher percentage of their income online compared to participants from higher income classes. As such, a general familiarity with e-commerce transactions can be expected for all income groups.

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<sup>30</sup> In the resulting sub-sample of 14260 transactions, only 144 of the top 200 mainstream e-commerce websites were represented (see Appendix I).

**Table 3. Demographic characteristics of sample (n=2,819)**

	Household income (US\$)				
	<25000	25000 - 49999	50000 - 74999	75000 - 99999	>=100000
<b>Age</b>					
18 - 24	32.1%	29.7%	26.1%	24.7%	25.4%
25 - 34	28.3%	23.7%	23.5%	21.4%	19.6%
35 - 44	16.3%	19.0%	18.8%	23.6%	18.2%
45 - 54	12.9%	14.3%	12.0%	14.0%	19.9%
55 - 64	7.3%	9.1%	11.0%	8.7%	10.7%
65+	3.1%	4.2%	8.6%	7.6%	6.3%
<b>Gender</b>					
Female	50.1%	50.7%	50.9%	51.1%	44.8%
Male	49.9%	49.3%	49.1%	48.9%	55.2%
<b>Household size</b>					
1 person	14.4%	11.9%	9.3%	11.5%	10.1%
2 people	23.2%	28.5%	28.5%	25.8%	22.8%
3 people	22.8%	17.6%	17.3%	21.4%	23.7%
4 people	15.1%	17.5%	20.9%	21.9%	19.4%
5 people	17.2%	17.8%	16.7%	12.9%	20.1%
6+ people	7.3%	6.7%	7.3%	6.5%	3.9%
<b>Internet use</b>					
<5 hours / week	15.1%	18.4%	19.5%	20.5%	20.8%
5-16 hours / week	44.9%	40.1%	43.1%	40.5%	44.3%
>16 hours / week	40.0%	41.5%	37.4%	39.0%	34.9%
<b>Transactional data</b>					
Ø number of transactions	4.6	4.8	5.4	5.1	5.7
Ø overall spend (US\$)	163.4	167.4	201.3	202.6	230.7

### 3.2 Measurement development

#### 3.2.1 Dependent variables: E-commerce use

To study the aspects of e-commerce platform diversity and the use of supporting e-commerce features, we developed a total of six dependent variables (DV). We operationalized the DVs in the following manner:

*DV1: Platform use diversity.* To measure platform use diversity, we assessed the degree to which an individual diversified their transactions (a) across different websites within each e-commerce platform, (b) across different e-commerce platforms, and in terms of (c) the share of transactions on alternative platforms.

*DV1a-b: Across-website & across-platform diversity.* We adapted an entropy measure of diversification (Jacquemin & Berry, 1979) from the field of corporate diversification to

evaluate a user's spread of transaction activity across different e-commerce platforms and websites. The key advantage of this diversification index is that it combines the benefits of a frequency-type measure with the added insight of a classification scheme (Palepu, 1985). Due to this feature, the total diversification can be further disaggregated into *(DV1a) across-website* and *(DV1b) across-platform* diversity. It is calculated as follows (Palepu, 1985):

$$DT = DR + DU = \sum_{j=1}^M P^j \left( \sum_{i \in j} P_i^j \ln \frac{1}{P_i^j} \right) + \left( \sum_{j=1}^M P^j \ln \frac{1}{P^j} \right)$$

where  $DT$  = total diversification;  $DR$  = across-website diversification;  $DU$  = across-platform diversification;  $j = 1, \dots, M$  = e-commerce platforms;  $P^j$  = share of transactions on platform  $j$ ; and  $P_i^j$  = share of transactions on domain  $i$  within platform  $j$ .

*Across-website diversity* captures the spread of a user's transaction activity across websites on a given e-commerce platform, for example, specialized retailers. A user who, for instance, buys a pair of shoes at each of the online footwear retailers Footlocker.com and Zappos.com will score higher than a comparable user who buys both pairs at Zappos.com. *Across-platform diversity* in turn measures the spread of a user's transaction activity across the six e-commerce platforms defined for the purpose of this study. A user who, illustratively, purchases two pairs of Nike sneakers, one on Nike.com – a brand shop – and the other on Amazon.com – a general retailer – will again have a higher diversification score than a comparable user who purchases both pairs on Amazon.com. Furthermore, both measures take into account a user's total number of transactions within and across platforms, thereby controlling for pure volume-driven diversity.

*DV1c: Share of transactions on alternative platforms.* To validate the spread of transactions between mainstream (general retailer, specialized retailer, brand shop) and alternative e-commerce platforms (daily deals, flash sales, auctions), we developed a second measure of diversity by calculating a user's share of transactions on alternative e-commerce sites in relation to the user's total number of transactions. Taking into account the data distribution, we clustered the results into six categories (0, 0.1%-25%, 25-49.9%, 50-74.9%, 75-99.9%, 100%) to enable a meaningful differentiation between non-users, occasional users and those for whom alternative platforms are an integral part of their shopping behavior. On the one hand, this serves to corroborate the entropy measure of diversification postulated above. On the other, it extends the concept of diversity by evaluating whether a user simply uses a broad range of

mainstream e-commerce sites or, in fact, leverages alternative e-commerce platforms as well, which typically offer large discounts.

*DV2: Use of supporting e-commerce features.* Searching for e-coupons and product prices can be observed as part of an information search taking place before a transaction (Pavlou & Fygenon, 2006). Following previous research (Johnson, Moe, Fader, Bellman, & Lohse, 2004), we defined a pre-purchase period of three days prior to the transaction to cover the longitudinal aspect of searching and to avoid inadvertently including non-transaction-related searches at the same time. This timespan appears reasonable given the need for prices and e-coupons to be transaction-related and up-to-date. Search theory (Diamond, 1989) suggests that a search will only be executed if its marginal benefit is expected to exceed its marginal cost. Thus, we measured the use of supporting e-commerce features only for transactions with a value of at least US\$ 50 to ensure a sufficiently high incentive for all income groups to search. Applying this condition resulted in a sub-sample of 1195 users. Three aspects related to supporting e-commerce features were measured:

- *DV2a:* The number of transactions for which the participant accessed price comparison sites within a period of three days prior to the transaction, aggregated over six months
- *DV2b:* The number of transactions for which the participant accessed e-coupon sites within a period of three days prior to the transaction, aggregated over six months
- *DV2c:* The number of transactions for which the participant accessed both price comparison and e-coupon sites within a period of three days prior to the transaction, aggregated over six months

In the subsequent statistical regression model, these count variables of the number of transactions in which a supporting e-commerce feature was used were put in relation to the user's total number of transactions within the six month period via an exposure variable in order to account for the proportionate level of use.

### ***3.2.2 Independent variable: Socio-economic status***

Socio-economic status is generally defined based on household income and education level (Jung et al., 2001; Lenhart, 2002). Given that household income is viewed as the strongest indicator of standard of living (Duncan, Daly, McDonough, & Williams, 2002) and that education has been shown to be highly indicative of household income (Chiou-Wei & Inman,

2008), in this study we operationalized socio-economic status on the basis of household income. Participants' household income was operationalized as an ordinal scale (1-5) in US\$ 25000 increments. Household rather than individual income was used because an individual's socio-economic status is generally highly dependent on the overall economic welfare of their household. Furthermore, household income is a useful indicator particularly for women, who may not be the primary earners in the household (Galobardes, Shaw, Lawlor, Lynch, & Davey Smith, 2006).

### **3.2.3 Control variables**

We controlled for the demographic variables age, gender and household size. Age and household size were operationalized as continuous variables and gender as a binary variable (men = 0, women = 1). Furthermore, we took into account potential rural-urban<sup>31</sup> disparities in online shopping behavior that may be driven by differences in access, availability of products and social norms (Lennon et al., 2007). This was included as a binary variable (urban = 1, rural = 0). In addition, we also controlled for Internet use intensity (measured on a three-point scale ranging from 1 = "<5 hours per week" to 3 = "16+ hours per week), which has been shown to be a strong predictor of online buying (Goldsmith, 2002). Finally, when evaluating the use of supporting e-commerce features, we accounted for an individual's familiarity with e-coupon and price comparison sites by controlling for prior visits to such sites outside of the three-day period prior to a transaction.

### **3.3 Selection of statistical methods**

To account for differences in the composition of our six dependent variables, we used ordinary least squares (OLS), ordered logit and zero-inflated regression models to test our hypotheses. The two DVs related to the entropy measure of diversification (DV1a-b) exhibit properties of a continuous variable as well as linearity in parameters and were therefore treated using linear multiple regression. For DV1c, which is operationalized as an interval variable, we used an ordered logit model to account for the discreteness of the DV. The model predicates that a series of breakpoints exist between the DV categories (McKelvey & Zavoina, 1975), as is the case for DV1c.

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<sup>31</sup> The United States Census Bureau (2010) identifies two types of urban areas: urbanized areas (UAs) of 50,000 or more people and urban clusters (UCs) of at least 2500 and fewer than 50000 people. We consider both types as being "urban" for our analysis. "Rural" encompasses all population, housing, and territory not included within these urban areas. The ZIP Code Tabulation Area (ZCTA) relationship file provided by the US Census Bureau is used to match the 2010 Census urban-rural classification with the ZIP codes provided in the clickstream dataset.



DV2a-c were operationalized as count variables and required special consideration. The discrete, nonlinear and nonnegative integer properties of count data imply that the parametric assumptions of an OLS regression would result in biased results. A Poisson distribution is much better suited to model count data because it is also a discrete distribution and takes on a probability value only for integer values of 0 or greater (Coxe, West, & Aiken, 2009).

When using Poisson regression models, it is important to account for variable lengths in the observation periods. Unless otherwise specified, Poisson models assume equal observation periods. This was not the case in our data, where the number of times that a user accessed a price comparison and/or e-coupon website in connection with a transaction is highly dependent on the user's total number of transactions. Given that the participants in our sample executed anywhere between one and 78 transactions over the tracking period of six months, this aspect needed to be accounted for. One option was to transform the DV into a rate and use a linear regression model. However, the OLS regression assumption of conditional normality of the errors may be violated and the method might hence yield biased results (Coxe et al., 2009). A generally preferable approach is to use an expansion of the Poisson model that includes an offset to control for exposure. This approach ensures that the correct probability distribution is maintained and that the error structure assumptions are fulfilled. Algebraically, the variable observation period is incorporated into the loglinear Poisson regression function by taking the natural logarithm of the exposure  $t$  and constraining its coefficient to 1, as derived below (Coxe et al., 2009). In our regression models for DV2a-c, we included the total number of transactions by each user as an exposure variable.

$$\ln(\hat{\mu}/t) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$$

$$\ln(\hat{\mu}) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p + \ln(t)$$

where  $\hat{\mu}$  is the predicted count on the response variable,  $X_1, X_2, \dots, X_p$  are the predictors,  $\beta_1, \beta_2, \dots, \beta_p$  are the regression coefficients and  $t$  is the exposure.

Another common problem with count data is overdispersion, the situation in which the (conditional) variance exceeds the (conditional) mean (Cameron & Trivedi, 2009). In this case, it is still possible to obtain consistent coefficient estimates using a Poisson regression, but the standard errors will be deflated<sup>32</sup> and the t-statistics inflated (Cox, 1983). In our price

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<sup>32</sup> The standard errors will only be deflated for data that fits the assumptions of a Poisson distribution and not for special cases, for example high incidence rates of zero.

comparison and e-coupon site use dataset, we observed that the data was strongly skewed to the right with a large number of excess zeroes. The comparably large differences between variances and means for DV2a-c, as shown in the descriptive statistics in Table 4, strengthened the impression of overdispersion. A likelihood ratio test using a negative binomial regression confirmed the suspicion. For all three DV2a-c, the overdispersion parameter alpha is different from zero and significant at  $p < 0.001$ .

**Table 4. Descriptive statistics for DV2a-c**

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Var.</b>	<b>Min.</b>	<b>Max.</b>
DV2a. Price comparison use	1195	.320	.882	.777	0	11
DV2b. Coupon use	1195	.228	.857	.734	0	10
DV2c. Coupon and price comparison use	1195	.065	.454	.207	0	9

Given the presence of overdispersion and excess zeroes in the sample, the most appropriate model to use is the zero-inflated Poisson (ZIP) model. The ZIP model is able to handle data with excess zeroes relative to the Poisson model by supplementing a count density with a binary process (Cameron & Trivedi, 2009). Vuong's likelihood ratio test (1989) for model selection confirmed the use of a zero-inflated model over a Poisson model in all instances.

#### **4. Results**

Table 5 displays summary statistics and pairwise correlations for the variables in our study. No indications of multicollinearity could be found, which means that the independent variables were sufficiently unrelated and the standard errors were not biased as a result. The pairwise correlations between DV2a, DV2b and DV2c were the only ones that exceed 20%. This is not critical, however, because these DVs are not used within the same regressions and the correlation level is still low enough to warrant individual variables.

**Table 5. Descriptive statistics and pairwise correlations**

Variables	Mean	S.D.	1	2	3	4	5	6
1 Age	3.69	1.51	1					
2 Gender	0.50	0.50	.08 *	1				
3 Household size	3.23	1.46	-.15 *	.06 *	1			
4 Internet use intensity	2.21	0.73	-.07 *	-.05 *	.10 *	1		
5 Urban/rural	0.72	0.45	-.09 *	-.04 *	.01	.08 *	1	
6 Household income	2.65	1.37	.11 *	-.02	.02	-.05 *	.09 *	1
7 DV1a. Across-website div.	0.09	0.22	.07 *	.08 *	-.02	.06 *	-.00	.06 *
8 DV1b. Across-platform div.	0.14	0.28	.07 *	.09 *	-.03	.03	-.02	.04 *
9 DV1c. Share alternative platforms	0.25	0.98	.01	.03	-.02	-.02	.01	.04
10 DV2a. Use of price comp.†	0.32	0.88	.09 *	.03	.03	.09 *	.00	.06 *
11 DV2b. Use of e-coupons†	0.23	0.86	.00	.08 *	.03	.11 *	.03	.06 *
12 DV2c. Use of both p.c. and e-c.†	0.07	0.45	.01	.06 *	.05	.10 *	.01	.06

Variables	7	8	9	10	11	12
7 DV1a. Across-website div.	1					
8 DV1b. Across-platform div.	.20 *	1				
9 DV1c. Share alternative platforms	-.03	.10 *	1			
10 DV2a. Use of price comp.†	n/a	n/a	n/a	1		
11 DV2b. Use of e-coupons†	n/a	n/a	n/a	.35 *	1	
12 DV2c. Use of both p.c. and e-c.†	n/a	n/a	n/a	.54 *	.65 *	1

† Pairwise correlations for DV2a-c are based on the sub-sample n=1195; \*p<0.05;

Note: Pairwise correlations between DV1a-c and DV2a-c are not comparable due to different sample configurations

Tables 6 and 7 present the results of our analysis. Models 1, 3, 5, 7, 9 and 11 are the control models for each of the DVs investigated. Model 2 indicates that income has a positive and strongly significant ( $p<0.001$ ) effect on the across-website diversity measure. This finding supports H1a, in which we posit that users with higher incomes shop on a larger variety of websites within a given platform category. Model 4 indicates moderate support for H1b, in which we predict that higher income users are also more likely to shop on a larger variety of platforms. This finding is corroborated by Model 6, which shows a positive and significant ( $p<0.01$ ) effect from income on the use of alternative e-commerce platforms, supporting H1c. Furthermore, our findings validate hypotheses H2a-c. Model 8 indicates some support for a positive relationship between income and the use of price comparison sites (H2a). Model 10 corroborates the hypothesis that users with higher incomes will be more likely to use e-coupons in connection with a transaction (H2b). Finally, we also find strong evidence for the notion that income has a positive effect on the simultaneous use of both price comparison and e-coupon sites prior to a purchase (H2c).

**Table 6. Effects of household income on e-commerce platform use diversity**

Variables	H1a. Across-website diversification		H1b. Across-platform diversification		H1c. Alternative platform use	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age	.009 ***	.008 **	.012 **	.010 **	.020	.007
Gender <sup>1</sup>	.037 ***	.039 ***	.052 ***	.053 ***	.459 **	.473 ***
Household size	-.004	-.004	-.007	-.007	-.076	-.082
Internet use intensity	.023 ***	.024 ***	.018 *	.019 **	.036	.049
Urban/rural <sup>2</sup>	-.000	-.004	-.012	-.014	.028	-.014
Household income		.011 ***		.008 *		.133 **
F	9.40 ***	9.86 ***	9.23 ***	8.41 ***		
Adj. R <sup>2</sup>	.015	.019	.014	.016		
LR chi <sup>2</sup>					12.57 *	19.16 *

Models 1-4 are calculated using linear regressions; models 5 and 6 are calculated using ordered logit regressions; N observations = 2819; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) men = 0, women = 1; 2) rural = 0, urban = 1

Regression results including standard errors are presented in the Appendix;

Note 1: All regression models were also run with a squared age variable to test for a u-shaped effect. Extant results are validated, goodness of fit statistics are slightly lower;

Note 2: 236 out of 2568 households with more than one participating user in the sample. All models were also estimated for an adjusted sub-sample (N=2332) containing only single-user households to test for unobserved household-dependent effects. Results are confirmed for all regression models.

**Table 7. Effects of household income on use of supporting e-commerce features**

Variables	H2a. Price comparison		H2b. E-coupons		H2c. Combined usage	
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Age	-.022	-.036	-.100	-.119	-.005	-.463 *
Gender <sup>1</sup>	.013	-.008	.070	.010	-.210	-.753 *
Household size	.091	.080	.011	.017	.154	.206
Internet use intensity	-.036	-.033	.268	.246	-.131	-.192
Urban/rural <sup>2</sup>	.054	.063	-.197	-.286	.656	-.268
Prior site visits	18.0	17.9	17.2	17.4	18.2	17.5
Household income		.084 *		.130 **		.271 **
Total transactions	-----exposure term-----					
LR chi <sup>2</sup>	207.4 ***	211.8 ***	219.4 ***	226.7 ***	82.83 ***	88.96 ***
AIC	1304.1	1301.7	911.7	906.4	362.2	358.1
BIC	1370.2	1372.9	977.8	977.6	428.4	429.3

All models are calculated using zero-inflated poisson regressions (regression results including standard errors are presented in the Appendix); N observations = 1195; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001;

1) men = 0, women = 1; 2) rural = 0, urban = 1

In addition to these findings relating to income, one further aspect warrants mention. Our results indicate that Internet use intensity is not across the board a significant predictor of e-commerce use behavior as might be expected. While it does positively influence transaction platform diversity (DV1a-b), there is no evidence of a significant effect on the specific use of

alternative platforms, price comparisons, or e-coupons. This result is surprising because higher daily Internet use has been shown to lead to a higher digital literacy (Hargittai & Hinnant, 2008), which in turn influences the sophistication of technology use. In our data sample, however, we find that income is actually negatively correlated with Internet use intensity ( $p < 0.01$ ). This implies that use experience does not per se lead to more sophisticated use.

In summary, we find substantial support for our hypotheses that socio-economic status has a significant impact on how individuals use e-commerce. Our findings confirm that the socio-economically disadvantaged are less likely to fully exploit the opportunities that the e-commerce space has to offer, from the range of mainstream and alternative transaction platforms to supporting features such as price comparisons and e-coupons. Their inability to make use of these opportunities, which are tied to potential economic gains, means that the socio-economically disadvantaged are failing to maximize their consumer surplus online despite the fact that they are the most in need. Consequently, our study establishes that existing socio-economic disparities are perpetuated within the context of e-commerce and that digital inequality persists.

## **5. Discussion**

This study set out to explore how individuals differ in their use of e-commerce as a function of their socio-economic status and, if digital inequality can be observed in the realm of e-commerce. Our findings have substantial implications for theory. Some findings are related to digital inequality research in particular, while others apply to information systems research in general. Furthermore, we provide important insights for practitioners, both in the public policy sphere as well as in the business world.

### **5.1 Implications for theory**

#### **5.1.1 Digital inequality research**

For digital inequality research, our findings first and foremost underscore that digital inequality is a prevalent societal issue, which not only has a first-order effect related to inequality in technology access but also comprises a second-order effect resulting from inequality related to differential ICT use. Despite undisputed advances in providing ICT access (OECD, 2013), ICT in general and the Internet in particular have not yet realized their full potential as equal opportunity platforms (Hargittai, 2010). In fact, as an unintended societal consequence, the

Internet might even perpetuate socio-economic stratification. Some scholars maintain that this divide will disappear with increasing Internet access over time (Compaine, 2001). Our results, however, tell a different story: even at levels of comparable Internet access, individuals who are already socio-economically advantaged seem to exhibit different e-commerce use patterns than their disadvantaged peers, which may potentially result in greater benefits from e-commerce use. With the increasing pervasiveness of e-commerce applications in our everyday lives and the growing relevance of Internet based self-service solutions, for example for travel bookings, these differences in e-commerce use could further widen the economic welfare gap between the rich and the poor.

Moreover, this study is, to the best of our knowledge, one of the first to empirically test and validate the hypothesized e-commerce divide. Digital inequality specifically in the context of e-commerce has to date garnered limited attention from academic research but is of key importance given its immediate economic implications. Prior research (Riggins & Dewan 2005) has only theorized about how socio-economic status might negatively impact e-commerce use. Counter to expectations, our findings indicate that socio-economic status does not primarily determine if or how much individuals shop online but – more importantly – *how* individuals make use of e-commerce opportunities. These insights represent an important step towards a more comprehensive understanding of digital inequality in the context of e-commerce.

In addition, our novel concept of use diversity could be particularly relevant to digital inequality research across different ICTs because it captures individual use patterns in multi-channel, multi-application environments. The less diverse use patterns of socio-economically disadvantaged individuals found in the context of e-commerce may be indicative of behavior in a variety of technological contexts, in particular those that offer a broad range of use possibilities. Online job search, for instance, is another domain where diversity, i.e. using different applications such as online job portals, company homepages and professional networking sites, may be beneficial by increasing the likelihood of finding a job.

### ***5.1.2 Information systems research***

This study also has several important theoretical implications for information systems research in general. Most importantly, a major methodological contribution of our study is the introduction of clickstream data as an empirical basis for technology acceptance research. As

Straub and Burton-Jones (2007) have noted, one of the most critical methodological issues underlying TAM is the high risk of common method variance as a result of common-rater effects and self-report bias. Typically, respondents are asked to indicate both their attitude towards a particular ICT, for instance how useful they find it, and whether they use or intend to use it. Consequently, the bivariate correlations between DV and IVs risk being severely skewed. The use of clickstream data allows these methodological limitations to be overcome. In addition, clickstream data tracks actual rather than intended behavior over a sustained period of time and hence avoids problems with time-variant intentions and the potential unreliability of self-reported behavioral attitudes (Podsakoff et al., 2003), a common issue in information systems research. Furthermore, asking users to reflect on use removed from the use experience itself fails to capture automatic use states or patterns that occur outside of individuals' awareness (Dimoka, Pavlou, & Davis, 2011; Ortiz de Guinea & Webster, 2013). While clickstream data is not without its limitations (Bucklin & Sismeiro, 2009), technology acceptance researchers in particular stand to benefit from integrating clickstream data of actual use with self-report surveys measuring behavioral antecedents.

Furthermore, we develop a novel and more holistic perspective on e-commerce use. Drawing on Benbasat and Barki (2007) and Burton-Jones and Straub (2006), we propose that the operationalization of e-commerce use needs to go beyond the notion of a simple purchase and must account for the context in which a transaction takes place, which is seldom one dimensional. The advantages of such an extended behavioral operationalization of use lie in a "more faithful representation of usage activities that users engage in, [and] stronger links with salient outcome variables" (Benbasat & Barki, 2007). Our perspective on e-commerce use contributes to the understanding of online shopping in a more holistic and nuanced manner, in particular with regard to economic utility-enhancing activities. By differentiating between several potentially utility-enhancing aspects of e-commerce (i.e., diverse transaction platforms, price comparison sites, coupon sites), the proposed view enables us not only to illuminate use behavior on an aggregate level but also to examine individual aspects. This approach yields a more thorough understanding of which specific aspects of use are particularly relevant within a certain context and can lead to more targeted measures. In fact, within the specific context of digital inequality, a nuanced operationalization of use like the one proposed is not just important but critical in order to uncover *how* individuals differ in the way they shop online.

## **5.2 Implications for public policy and online businesses**

Above and beyond contributions to theory, our study has implications for policy makers and business practitioners alike. Understanding how socioeconomically advantaged and disadvantaged users differ in their use of e-commerce enables policy makers to potentially devise countermeasures and businesses to develop strategies to adequately cater to different societal groups.

On a public policy level, our study highlights that digital inequality continues to be a substantial societal issue, even in developed countries such as the United States. Despite the rapid increase in Internet access, Internet use behavior still differs between socio-economic groups and reinforces societal stratification. Given that the Internet can be a catalyst for economic development and – when used effectively – possesses the potential to equalize social disparities (Anderson et al., 1995), unleashing this potential should be a priority for public policy. More specifically, our findings highlight the importance of developing not only access-based initiatives but also of implementing use-oriented measures. Existing governmental initiatives targeting Internet use, such as the US National Broadband Plan, have largely focused on providing access. However, our study suggests that this is not sufficient to ensure the same online opportunities to all groups in society. The traditional assumption of homogeneous ability to use ICT needs to be replaced by a more nuanced understanding, leading to more tailored policies that take socio-economic status into account. Policy interventions focusing on Internet education and digital skills could help to bridge the current gap and could be added to the educational agenda in the context of broader ICT education at secondary schools, in particular in underprivileged districts. Furthermore, consumer protection agencies could be empowered to raise awareness and promote knowledge dissemination about Internet use in general and e-commerce in particular.

Online businesses and providers of e-coupon and price comparison sites could use the insights on differential e-commerce use between socio-economic groups to make their services more attractive to the socio-economically disadvantaged, who currently might not be key customers. By effectively targeting currently alienated socio-economic groups, businesses can potentially expand their customer base and generate additional revenue. For instance, our theorizing highlights that the key hurdles – particularly for the socio-economically disadvantaged – associated with shopping on a broad range of platforms are complexity and the perceived risk of creating a unique personal account for each website. In some cases, such as with flash sale



sites, users are required to sign-up before even being able to view the products on offer. An increased adoption of integrated single sign-on systems such as “Login with Amazon”, “Login with Facebook” and Google+ by online retailers could remove the frictions associated with accessing third-party websites. Instead of having to create and manage multiple unique accounts, users would be able to conveniently log into a variety of sites using only one set of credentials.

## **6. Limitations and further research**

We acknowledge some theoretical and empirical limitations to our study, which call for further research. Further, we highlight additional promising avenues for research originating from our findings.

A common critique in the technology acceptance research field has been the focus on explaining a single behavior conceptualized in a narrow manner (Benbasat & Barki, 2007) at one point in time. Such a one-dimensional view does not reflect the multifaceted uses of technology and the dynamism inherent in technological change. In today’s fast-paced digitalized world, the realm of online functionalities and possibilities is constantly evolving. While our proposed view on e-commerce use, including platform use diversity and supporting e-commerce features use, aims to capture online shopping more fully in its complexity and variety than current constructs, it makes no claim to being collectively exhaustive as it focuses solely on potentially economically beneficial activities. Moreover, in the context of this study, we theorized on the potential economic value add of using e-commerce features and shopping diversely based on extant research, but did not empirically test this relationship due to data restrictions. Thus, we urge subsequent research to refine and extend our concept of e-commerce use, and to validate the hypothesized economic benefits. In particular, e-commerce applications relating to services such as e-banking, insurance and peer-to-peer marketplaces for accommodation and travel are gaining importance and offer an interesting avenue for further research. An extended conceptualization of system use is, of course, not limited to the field of e-commerce. Applying a more in-depth conceptualization of system use to other technologies and information systems can provide a particularly rich basis for better understanding individual differences in use patterns and their implications. For example, social network use is a common subject of technology acceptance research that may benefit from more differentiated investigations into actual use patterns given the variety of possible ways to make use of social network sites. Use patterns could also be of particular interest within

organizational settings to study how effectively or efficiently employees engage with information systems.

Further, the notion of use diversity developed in this study can provide an insightful lens for information systems scholars seeking to capture ICT use in a multi-technology, multi-application environment. Potential applications could lie, for example, in studies on information search and browsing patterns – areas in which the complexity of online behavior is the relevant research variable. To this end, the entropy measure of diversification proposed in this study may serve future researchers as a useful measurement approach for measuring use diversity across a range of settings. The concept of use diversity may also be of interest to digital inequality researchers, especially with regard to the broader issue of complexity management. Recent digital inequality research has sought to explain the differential abilities of socio-economic groups to use the Internet by studying skill-related aspects such as online navigation and information search skills (van Deursen & van Dijk, 2011). However, more fundamental, cognitive-psychological drivers such as the ability to multitask or handle information overload may in fact lie at heart of why the socio-economically disadvantaged may be less likely to fully leverage the breadth of Internet opportunities available. Future research may benefit from exploring the connection between diversity in use patterns and digital inequality in more detail, both from a psychological and a skills perspective.

The clickstream data used in our study has a significant advantage in providing a clear measurement of the variance in actual use by avoiding typical weaknesses of cross-sectional data such as self-report bias and common rater effects (Podsakoff et al., 2003). In our case, this advantage comes with the trade-off of omitted respondent demographic information and the limitation that the motivations behind the observed behavior cannot be captured. Existing research on the impact of socio-economic status on the behavioral TAM dimensions allows us to theorize as to why the socio-economically disadvantaged are less likely to use certain functionalities. Empirical investigations into the behavioral antecedents of digital inequality within the specific context of e-commerce would contribute to further substantiating this theoretical basis. Moreover, while comScore undertakes substantial measures (as described previously) to prevent potential sample bias, a certain degree of pre-selection bias might still exist. In addition, a stronger conceptualization of socio-economic status may be achieved by incorporating additional factors such as education and profession, which often – but not necessarily always – correlate with income. We therefore encourage the replication of our

findings using clickstream data in conjunction with a survey or structured interviews to enrich the understanding of the behavioral factors driving the differential behavior between advantaged and disadvantaged groups.

Moreover, the moderators that influence the effect of socio-economic status should be explored. Although we found no significant indications for the moderating effects of, for instance, gender, age, or the number of children in a household on our baseline associations, we encourage others to investigate these factors further. Correa, Straubhaar, Chen, and Spence (2013), for example, stress the positive impact that children have on their parents' adoption and use of the Internet. Innovation diffusion theory and research into the importance of social influence on technology adoption also highlight the critical effect of personal network exposure as a moderating variable, particularly with regard to the socio-economically disadvantaged (Hsieh et al., 2008). Understanding which factors can alleviate the impact of socio-economic status in the digital sphere has important implications not only for theory but also for policy making. For instance, the impact and effectiveness of interventional policy measures could be heightened if known moderating effects such as personal network exposure are appropriately leveraged. Future research could further elucidate the moderating impact of such situational factors on the structural determinants of digital inequality.

Furthermore, our research only captures online shopping behavior at home and in a voluntary environment. Given the spread of Internet-enabled mobile devices such as tablets and smartphones, online shopping is increasingly migrating from the traditional household PC to other platforms and locations. Most notably, individuals are increasingly leveraging their mobile devices to undertake price comparisons and online transactions while in traditional brick-and-mortar stores or on the go (Shankar, Venkatesh, Hofacker, & Naik, 2010). Future research should take into account the omni-channel nature of digital functionalities such as e-commerce and investigate how use patterns differ across channels. Moreover, the differences in e-commerce use patterns observed occurred in a voluntary setting and were tracked only passively. Scholars should investigate whether differential use patterns persist if online use is mandatory as might be the case for some e-government uses.

Finally, we encourage further research to test the generalizability of our findings. Technology acceptance patterns have been found to be influenced, for example, by culture (Im, Hong, & Kang, 2011). It would be prudent to examine to what extent our findings from the US can be replicated in other countries with similar levels and a similar history of Internet access, such as

many European nations. Cultural idiosyncrasies, such as German thriftiness for instance, may have a moderating effect on the pervasiveness of digital inequality in e-commerce. Furthermore, a longitudinal panel study across several years could yield interesting insights into how differences in e-commerce use patterns between socio-economic groups evolve over time and whether evidence of convergence can be found. Such a longitudinal perspective could allow extrinsic factors such as learning to be tested.

## **7. Conclusion**

This study presents a new perspective on how ICT in general and e-commerce in particular relate to the societal phenomenon of digital inequality. Following the call by researchers to better understand the field of e-commerce in the context of digital inequality, we introduce a nuanced perspective on potentially, economically beneficial e-commerce use and investigate how individuals from different socio-economic backgrounds differ in their online shopping behavior. We empirically examine this behavior using clickstream data. Our findings reveal that despite equal access, significant differences in e-commerce use behavior between the socio-economically advantaged and disadvantaged exist. Although Internet applications such as e-commerce possess an equalizing power and could serve as a potent catalyst to reduce existing socio-economic disparities in both the online and the offline world, this potential is so far not being realized. In this respect, our research constitutes an important step towards a better understanding of how ICT can impact our society for better or worse and the development of measures to influence this impact.

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Appendix

**Table A1. Effects of household income on e-commerce platform use diversity (with standard errors)**

Variables	H1a. Across-website diversification		H1b. Across-platform diversification		H1c. Alternative platform use	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age	.009 *** (.003)	.008 ** (.003)	.012 ** (.004)	.010 ** (.003)	.020 (.048)	.007 (.048)
Gender <sup>1</sup>	.037 *** (.008)	.039 *** (.008)	.052 *** (.011)	.053 *** (.011)	.459 ** (.146)	.473 *** (.146)
Household size	-.004 (.003)	-.004 (.003)	-.007 (.004)	-.007 (.004)	-.076 (.050)	-.082 (.050)
Internet use intensity	.023 *** (.006)	.024 *** (.006)	.018 * (.007)	.019 ** (.007)	.036 (.099)	.049 (.099)
Urban/rural <sup>2</sup>	-.000 (.009)	-.004 (.009)	-.012 (.012)	-.014 (.012)	.028 (.159)	-.014 (.160)
Household income		.011 *** (.003)		.008 * (.003)		.133 ** (.051)
F	9.40 ***	9.86 ***	9.23 ***	8.41 ***		
Adj. R <sup>2</sup>	.015	.019	.014	.016		
LR chi <sup>2</sup>					12.57 *	19.16 *

Models 1-4 are calculated using linear regressions; models 5 and 6 are calculated using ordered logit regressions; N observations = 2819; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) men = 0, women = 1; 2) rural = 0, urban = 1

**Table A2. Effects of household income on use of supporting e-commerce features (with standard errors)**

Variables	H2a. Price comparison		H2b. E-coupons		H2c. Combined usage	
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Age	-.022 (.051)	-.036 (.051)	-.100 (.067)	-.119 (.066)	-.005 (.248)	-.463 * (.220)
Gender <sup>1</sup>	.013 (.146)	-.008 (.145)	.070 (.167)	.010 (.168)	-.210 (.390)	-.753 * (.384)
Household size	.091 (.047)	.080 (.047)	.011 (.048)	.017 (.049)	.154 (.094)	.206 (.116)
Internet use intensity	-.036 (.102)	-.033 (.101)	.268 (.148)	.246 (.148)	-.131 (.366)	-.192 (.563)
Urban/rural <sup>2</sup>	.054 (.166)	.063 (.166)	-.197 (.198)	-.286 (.200)	.656 (.606)	-.268 (.668)
Prior site visits	18.0 (651)	17.9 (626)	17.2 (373)	17.4 (394)	18.2 (966)	17.5 (662)
Household income		.084 * (.040)		.130 ** (.048)		.271 ** (.106)
Total transactions	-----exposure term-----					
LR chi <sup>2</sup>	207.4 ***	211.8 ***	219.4 ***	226.7 ***	82.83 ***	88.96 ***
AIC	1304.1	1301.7	911.7	906.4	362.2	358.1
BIC	1370.2	1372.9	977.8	977.6	428.4	429.3

All models are calculated using zero-inflated poisson regressions; N observations = 1195; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) men = 0, women = 1; 2) rural = 0, urban = 1

The following list of websites encompasses the e-commerce related domains accessed by the users in the clickstream data sample over the period of six months. The domains were classified in one of the following disjoint categories: general retailers, specialized retailers, brand shops, auctions, daily deals, flash sales, price comparisons and e-coupons. The classification was undertaken by two independent raters, who received the same platform descriptions and selection criteria.

**Table A3. Classification of Internet domains**

**General retailer:** Website offering a wide range of products not limited to one brand or one product type. Purchase transactions can be undertaken directly on the website at a fixed price (no bidding).

aafes.com	hsn.com	qvc.com
amazon.com	jcpenny.com	samsclub.com
buy.com	kmart.com	seventhavenue.com
costco.com	kohls.com	shopnbc.com
fingerhut.com	lakeside.com	staples.com
ginnys.com	macys.com	target.com
google.com	newegg.com	tigerdirect.com
yahoo.com	overstock.com	walmart.com

**Specialized retailer:** Website specialized in one type of product (e.g., shoes) and with multiple brands on offer. Purchase transactions can be undertaken directly on the website at a fixed price (no bidding).

123inkjets.com	dillards.com	nordstrom.com
1800contacts.com	drsfostersmith.com	officedepot.com
1800petmeds.com	drugstore.com	officemax.com
6pm.com	dsw.com	orientaltrading.com
americangirl.com	eastbay.com	puritan.com
amway.com	ecampus.com	quill.com
autopartwarehouse.com	eddiebauer.com	radioshack.com
basspro.com	endless.com	rei.com
bathandbodyworks.com	etsy.com	safeway.com
bedbathandbeyond.com	express.com	saksfifthavenue.com
bestbuy.com	finishline.com	shoebuy.com
bhphotovideo.com	footlocker.com	shoes.com
blair.com	fragrancenet.com	sierratradingpost.com
bloomingdales.com	frys.com	sportsauthority.com
bodybuilding.com	gamefly.com	stubhub.com
boostmobilestore.com	gamestop.com	tennis-warehouse.com
cabelas.com	gymboree.com	t-mobile.com
ccs.com	homedepot.com	toysrus.com
cduniverse.com	jr.com	tracfone-orders.com
checksunlimited.com	landsend.com	verizonwireless.com
childrensplace.com	lanebryant.com	visiondirect.com
christianbook.com	llbean.com	vitacost.com
collectionsetc.com	lowes.com	womanwithin.com
danscomp.com	metropcs.com	zales.com
diapers.com	midnightvelvet.com	zappos.com
dickssportinggoods.com	mycricket.com	



**Brand shop:** Website offering a range of products dedicated to one brand. Purchase transactions can be undertaken directly on the website at a fixed price (no bidding).

abercrombie.com	disneystore.com	norton.com
abercrombiekids.com	element5.com	ralphlauren.com
ae.com	epson.com	roamans.com
aeropostale.com	forever21.com	sears.com
aitsafe.com	gap.com	sephora.com
apple.com	hp.com	sony.com
att.com	intuit.com	sprint.com
avon.com	jcrew.com	swansonvitamins.com
barnesandnoble.com	kay.com	talbots.com
bizsiteservice.com	kingsizedirect.com	toshibadirect.com
bose.com	lenovo.com	victoriasscret.com
cartserver.com	mcafee.com	vistaprint.com
coach.com	melaleuca.com	wetseal.com
coldwatercreek.com	mlb.com	
dell.com	nflshop.com	

**Auction site:** Websites offering a wide range of products not limited to one brand or one product type. Purchase via auction/bidding process with the possibility of direct purchase at a fixed price.

cqout.com	govsales.gov	ubid.com
ebay.com	listia.com	webidz.com
ebid.com	onlineauction.com	webstore.com
epier.com	shopgoodwill.com	

**Daily deal site:** Website offering virtual vouchers for a limited time for a selection of discounted goods and services that are typically local and may be employed offline. A transaction entails the purchase of a voucher rather than the direct product or service.

groupon.com	livingsocial.com	eversave.com
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**Flash sale site:** Website offering a limited stock of discounted (often brand-name) products. Purchase transactions can be undertaken directly on the website at a fixed price (no bidding).

beyondtherack.com	hautelook.com	ideeli.com	ruelala.com
editorscloset.com	modnique.com		thefoundary.com
fab.com	myhabit.com		theoutnet.com
fashionvault.com	onekingslane.com		therealreal.com
gilt.com			yoox.com

**Price comparison engine:** Website with a search engine that aggregates product listings from different retailers. Products or services cannot be purchased directly on this website.

google.com/shopping	shopping.com	pronto.com
nextag.com	shopzilla.com	thefind.com
pricegrabber.com	become.com	bizrate.com

**E-coupon sites:** Website that aggregates free promotional savings codes that can be applied to a purchase transaction on another e-commerce website. Products or services cannot be purchased directly on this website.

groupon.com/coupons	slickdeals.com	eversave.com
retailmenot.com	ebates.com	smartsources.com
shopathome.com	fatwallet.com	couponcabin.com
coupons.com	bradsdeals.com	dealcatcher.com
livingsocial.com/coupons	savings.com	valpak.com

# **Bridging digital inequality: What can public policy makers do to ensure equal benefit from online opportunities?**

*Katharina Buhtz, Annika Reinartz*

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## **Abstract**

The global penetration of digital technologies has grown rapidly over the last two decades and has been the source of many opportunities. Yet as more and more aspects of our lives shift online, concerns are being voiced that being online is becoming a prerequisite to fully participate in society and that some people may be digitally excluded. This so-called "digital inequality" carries the risk of potentially exacerbating social inequality and, despite improvements in access, remains a relevant phenomenon to this day. The present article illuminates how digital inequality has evolved over time and how it manifests itself in different domains such as education and employment. Building on a qualitative case study of online job search, the key factors leading to disengagement and digital exclusion are outlined. Based on these, recommendations targeted at public policy makers are derived, which may help to ensure that everyone can benefit equally from online opportunities.

**Keywords:** Digital inequality, technology acceptance, public policy implications, technology (dis-)engagement

Submitted to the Communications of the ACM (CACM)

## **1. Introduction**

The global penetration of the Internet has grown rapidly over the last two decades. Today, Internet-based information and communication technologies (ICT) permeate our daily lives. The most recent Pew Internet Life Project survey, for example, found that in 2014 90% of American adults and as many as 95% of American teens used the Internet. In addition, 64% of American adults own Internet-enabled smartphones. Similarly, 89% of Germans use the Internet, 76% do so daily (EUROSTAT, 2014). In line with this development, more and more products and services are shifting online to enhance or even substitute offline services: everything from groceries to cars to personal coachings can be bought and booked online. We can talk to e-doctors, find the best personal loan, search for health information, and find jobs online. We can attend online educational classes and learn from Youtube tutorials. We can stay connected with our social and professional networks via Whatsapp, Facebook or LinkedIn. With the rise and diffusion of smartphones, all of us can now access these services anywhere, anytime.

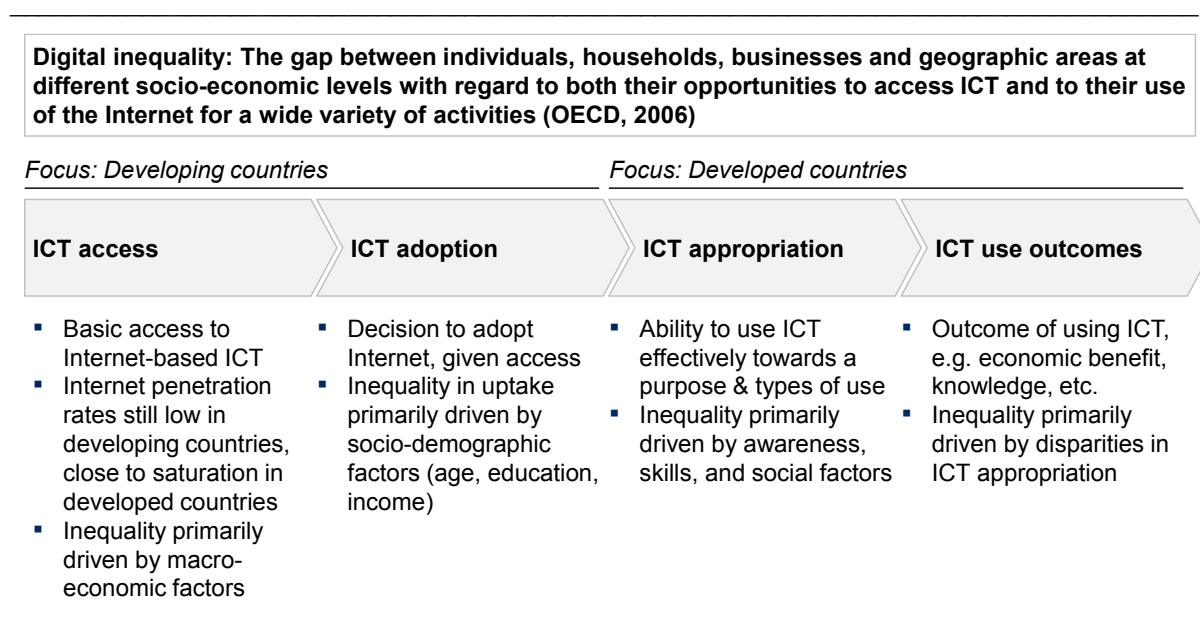
Yet as more and more aspects of our lives shift online, concerns are being voiced that in order to participate fully in society, “being online” is not enough – individuals have to be able to leverage the advantages that digital technologies offer. Very recently, Barack Obama warned that “in this digital age, when you can apply for a job, take a course, pay your bills ... with a tap of your phone, the Internet is not a luxury. It’s a necessity” (Superville, 2015). Moreover, a recent study by the German Institute for Trust and Security on the Internet (DIVSI) on Internet participation cautions that we may be facing a “new form of digital disparity” (2015, p. 7), one in which those individuals who are able to leverage online educational and economic opportunities stand to profit, while those who are not able to risk being sidelined, a phenomenon termed ‘digital inequality’. If not addressed, digital inequality may exacerbate social inequality by “improving the prospects of those who are already in privileged positions while denying opportunities for advancement to the underprivileged” (Hargittai, 2003). Policy makers need to understand what drives digital inequality and how smart policies can address this issue in order to ensure that all individuals can partake and benefit fully from the digital revolution.

In this vein, this practitioner-oriented paper aims to inform policy makers about the phenomenon of digital inequality, potential domains for digital opportunities that merit special policy attention, and success factors in devising measures to bridge the gap. It builds on key

insights from a qualitative case study of online job search in Germany to illustrate the mechanisms and factors that inhibit individuals from leveraging digital opportunities and the role governmental institutions can play in this context. In so doing, this paper contributes to conveying some of the key insights on digital inequality from academic research – extant, as well as new insights developed through own research – to a practitioner audience.

## 2. The issue of the digital inequality

The Organization for Economic Cooperation and Development (OECD) defines digital inequality as the “gap between individuals, households, businesses and geographic areas at different socio-economic levels with regard to both their opportunities to access ICT and to their use of the Internet for a wide variety of activities” (OECD, 2006). More specifically, four levels of digital inequality exist: inequalities with respect to ICT access, ICT adoption, ICT appropriation, and ICT use outcomes (Figure 1).

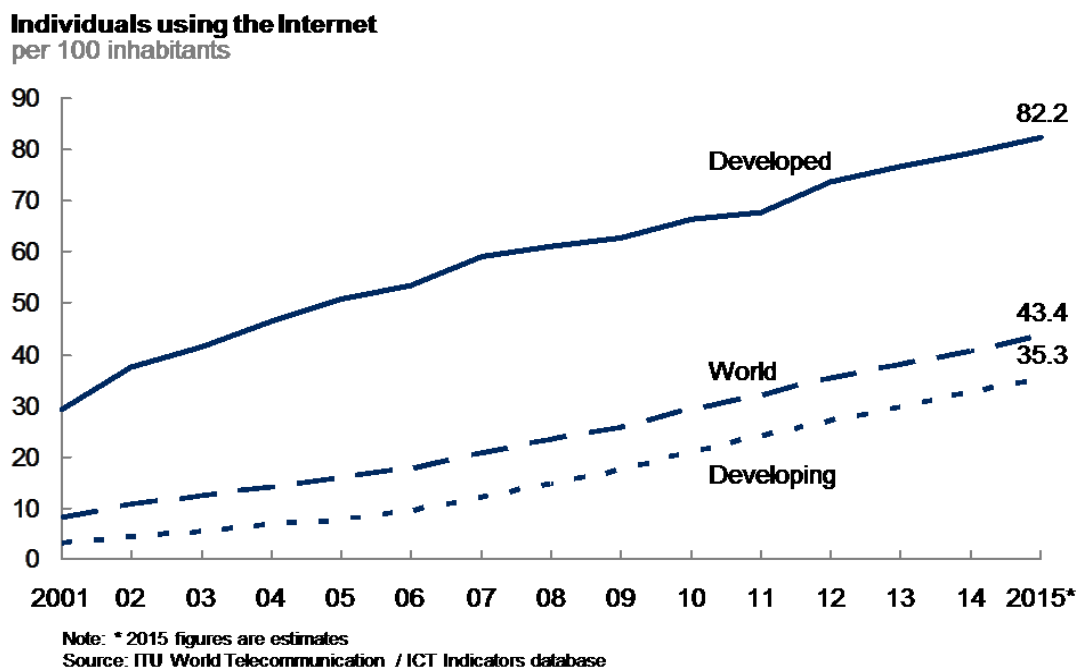


**Figure 1. Levels of digital inequality along the ICT adoption cycle**

### 2.1 Digital inequality with respect to ICT access and adoption

Limited access or limited possibilities to use the Internet are at the root of the digital inequality issue. In fact, the high Internet penetration rates particularly in developed countries hide the fact that there are still 4,2 billion individuals worldwide who remain offline – by circumstance or by choice (ITU, 2015). As shown in Figure 2, in particular large parts of the developing world still remain unconnected or unable to use the Internet. While Internet penetration rates

in developed countries such as the U.S., the Netherlands or Germany are approaching full coverage, many sub-Saharan, African countries struggle with Internet penetration rates as low as one or two percent, e.g. Eritrea, Burundi or Somalia (ITU, 2015). Generally, disparities in ICT penetration can not only be observed between developing and developed countries (Dewan et al., 2010) but also within groups of similar country clusters like the European Union (Cruz-Jesus, Oliveira, & Bacao, 2012), e.g., with less than 60% of Italians and Greeks being connected to the Internet in 2014. Research has found that a country's wealth, level of education, demographic situation, infrastructure, cost factors and governmental regulation have a major impact on Internet penetration.



**Figure 2. Individuals using the Internet per 100 inhabitants**

Furthermore, a range of socio-demographic factors have been found to impact digital inequality within a certain society, with age and socio-economic status being the most significant determinants (Boase, 2010; Hsieh et al., 2011). For instance, the D21 Digital Index for Germany illustrates that despite high overall penetration rates, major differences exist in Internet use between individuals of different income, education, and age. While almost 94% of those with a monthly income higher than 3000 Euros used the Internet, only 54% of those with a monthly income lower than 1000 Euros were online in 2014. Similarly, 98% of those younger than 30 years were Internet users in 2014, while the user rate drops to 64% and 29% for those

older than 60 years and 70 years respectively. These statistics show that in developed countries, like Germany, differences in Internet adoption may exist among certain socio-demographic groups, but the overall level of Internet penetration nevertheless remains high.

## **2.2 Digital inequality with respect to ICT appropriation and use outcomes**

In countries with high Internet penetration rates, digital inequality primarily manifests itself in the form of differences in ICT appropriation and ICT use outcomes. More specifically, individuals differ in how they appropriate ICTs and the degree to which they are able to leverage digital opportunities for their own benefit. Van Deursen and Van Dijk (2010) found that skills play an instrumental role in determining how effectively individuals are able to appropriate digital technologies and differentiate between medium-related skills (i.e. operating a device) and content-related skills (i.e. navigating multiple websites in a goal-directed manner). Others have found that the socio-economically disadvantaged use digital technologies less for ‘capital-enhancing’ activities, such as reading news or health information online (Hargittai & Hinnant, 2008). These apparent differences in ICT appropriation highlight that merely providing access to digital technologies does not ensure that individuals are able to profit equally from them.

In fact, unequal ICT appropriation often translates into unequal outcomes, which can affect individuals in multiple ways. It has been suggested, for instance, that digital inequality may lead to an economic opportunity divide resulting from the digitally disadvantaged’s lesser ability to leverage Internet-based education, training, and employment opportunities (Mossberger et al., 2003). Similarly, researchers found that not being able to effectively use ICTs can have detrimental effects on academic achievements, health outcomes and social outcomes (Chen et al., 2014; Hampton, 2010; Wei et al., 2011). The benefits of using – and the repercussions of not using – digital technologies are becoming increasingly apparent. Online job platforms, for instance, are projected to increase employment globally by 72 million full-time-equivalent positions by more effectively connecting individuals with work opportunities (Manyika et al. 2015). Individuals who are unable to fully appropriate digital technologies such as these may find themselves disadvantaged, both online and offline. As digital technologies pervade more and more areas of daily life, this issue only becomes more relevant.

### 3. Digital opportunities and their potential to decrease inequality

Against the backdrop of the ongoing digitization, we believe that there are a number of focal domains in which individuals are particularly likely to profit from digital opportunities – or be disadvantaged if they do not engage. Out of a range of applications, we identified six online domains that we believe to be particularly promising in enhancing one’s life chances: education, e-commerce, employment, e-government and public services, health, and finance and insurance. Figure 3 outlines the main digital opportunities that exist in each of these domains. In addition, we explore the domains of education and e-commerce in more detail in the following paragraphs and, in the next chapter, build on proprietary data from a qualitative case study of online job search in Germany to provide a comprehensive perspective on digital opportunities and mechanisms of (dis-)engagement in the employment domain.

Domain	Digital tools enable users to...	Examples of platforms or services
<b>Education</b>	<ul style="list-style-type: none"> <li>Provide cheaper, more convenient, flexible access to e-learning services and content</li> <li>Opens up formal education and accredited courses to non-traditional students</li> </ul>	MOOCs (e.g. Coursera, Udacity, Edx), Wikipedia, Youtube tutorials, online dictionaries, online coaches, Skillshare, Babbel
<b>E-commerce</b>	<ul style="list-style-type: none"> <li>Information advantage through easier access, ability to compare products and services, and greater price transparency</li> <li>Profit from increased convenience and supply</li> </ul>	Online shopping portals (Amazon), price comparison sites (Nextag), daily deal sites (Groupon), flash sale sites (Yoox, Gilt)
<b>Employment</b>	<ul style="list-style-type: none"> <li>Search for work opportunities based on extended matching attributes</li> <li>Provide transparency into company reputation, skills, and other traits</li> <li>Facilitate application process</li> <li>Connect via professional networks</li> </ul>	Monster, LinkedIn, Careerbuilder, Vault, Xing, company websites
<b>E-government/ public services</b>	<ul style="list-style-type: none"> <li>Facilitate communication &amp; collaboration</li> <li>Enable transactions of key services</li> <li>Simplify information access</li> </ul>	Online tax returns, business registration, scheduling of appointments at public agencies
<b>Health</b>	<ul style="list-style-type: none"> <li>Gain information about healthy lifestyles, diseases, health-related offerings and services</li> <li>Discuss, research and share health-related issues</li> <li>Conveniently leverage fitness and health tutorials and coaching</li> </ul>	Runtastic, Oscar Health, e-doctors, Youtube tutorials, medical forums, patient-centered online follow-up care, TK Gesundheitscoach
<b>Finance and insurance</b>	<ul style="list-style-type: none"> <li>Achieve savings through online comparison of services prices and product offers</li> <li>Circumvent bank fees (e.g. for offline services)</li> <li>Gain access to alternative/ non-traditional sources of credit, savings, and insurance</li> </ul>	Paypal, Transferwise, Zencap, Weltsparen, e-only banks (DKB), Auxmoney, Money Saving Expert

**Figure 3: Digital opportunities and their potential to decrease inequalities**

One focal domain is education, where e-learning is revolutionizing the access to and cost of schooling and education. Analysts project that global revenues from online learning will reach USD 51 billion by 2016 (Ambient Insight Research, 2013).

- *What are the benefits?* E-learning can dramatically increase the availability of formal and informal educational content to underserved population segments. Digital inequality particularly affects individuals with lower incomes and lower educational backgrounds, who often cannot afford to pursue higher education. Online education, for example in the form of massive online open courses (MOOC), is openly accessible to anyone with an Internet connection, offers accredited courses at low or no cost, and allows flexible, remote learning which is easily compatible with part-time work. Through this model, MOOCs open up (higher) education particularly to non-traditional students and reach a wider share of the population. More generally, students can achieve better educational outcomes by leveraging digital content such as online dictionaries, language or math coaches, and Youtube tutorials. Particularly if parents are not able to support their children in their studies, e-learning resources can be of great help.
- *What are the challenges?* For socio-economically disadvantaged individuals, e-learning and MOOCs provide a promising avenue through which they can improve their educational achievements – and, as a consequence, economic – prospects. Yet for those who are digitally disadvantaged, the barrier to using these platforms may seem high, particularly when confronted with video conferences, online assignments, and community discussion forums as an integral medium of online learning. Internet access at home and connectivity speed may also be barriers to use. Policy makers and educational providers should ensure that the barriers to participation are kept as low as possible, for instance by offering view on demand rather than live streaming tutorials, which can be an issue where Internet connectivity is low, and providing adequate support structures.

Another focal domain in which digital technologies provide a critical advantage is e-commerce. In a broad sense, e-commerce can be understood as the range of products and services that can be purchased online.

- *What are the benefits?* E-commerce platforms offer consumers significant opportunities in terms of variety, economic savings, and convenience. Online retailers such as Amazon, for instance, offer millions of items, whereas a typical Wal-Mart Supercenter only carries around 125,000 distinct items (Barr, 2013). Moreover, greater price transparency and competition mean that online prices are, on average, ten percent lower than offline prices (Manyika & Roxburgh, 2011). Quick and convenient access to a vast amount of information about products and services, such as customer reviews, further helps to reduce the information asymmetry consumers are typically subject to.



- *What are the challenges?* The e-commerce world is complex, with a multitude of price comparison, daily deal and flash sale sites that offer discounts, as well as an overwhelming amount of information to filter through. Awareness of the manifold opportunities to profit from online discounts is the most common barrier for the digitally disadvantaged, along with the real and perceived risk of fraud. Policy makers should promote greater transparency regarding what e-commerce platforms exist, how to find and take advantage of the informational and economic opportunities available online, and the things to watch out for to minimize the risk of fraud. Online consumer awareness trainings may be one avenue through which this could be achieved.

#### **4. The case of online job search**

##### **4.1 Background on online job search**

Online job search stands out as a one domain where digital inequality is likely to affect individuals the most. How to search for jobs has dramatically changed over the last decade and the shift into the online sphere confronts individuals with the need to cope with multiple new Internet applications. While, in 2003, around 40% of vacancies in the 1000 largest German companies were still advertised in print media, this number diminished to 12% in 2014 (Weitzel et al., 2015). Today, over 90% of the companies use online channels to advertise vacancies and search for employees (BITKOM, 2010; Weitzel et al., 2015). Increasingly, firms are even shifting from online to mobile platforms for recruiting. Mobile platforms are expected to soon serve as the primary mechanism for communicating with job-seekers, pushing open jobs to applicant communities and attracting candidates. In fact, 28% of US companies report that they already see a large share of candidates applying for positions via mobile devices. Similarly, social professional networks are gaining momentum as key sources for finding talent for white-collar jobs, contributing a 46% share in the US (LinkedIn, 2015). A recent study by the McKinsey Global Institute (Manyika et al., 2015) estimates that, overall, up to 540 million individuals could profit from online talent platforms by 2025 through faster and more effective matching of open positions with job-seekers, a shift from informal to formal employment and the creation of marketplaces for contingency (freelance) work. For the labor market as a whole and for many individuals this potential is encouraging. At the same time, it highlights how imperative it is to ensure that the digitally disadvantaged are able to partake in this shift as offline channels increasingly are not only complemented but substituted by online and mobile

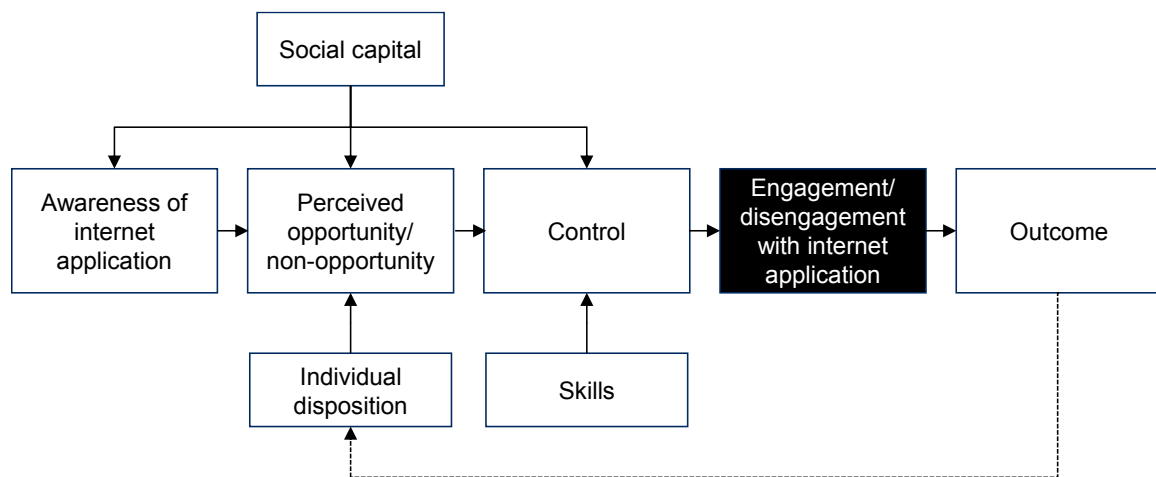
channels. If the digitally disadvantaged are not able to partake in this shift, they run the risk of being acutely disadvantaged in their job chances and socio-economic wellbeing.

#### **4.2 Description of our study**

Given its position as a focal domain of digital inequality, we undertook a qualitative case study of online job search in Germany in order to uncover which underlying mechanisms lead individuals to engage with, or disengage from, this Internet-based technology. We collected a broad set of data – comprising interviews, self-tests of online job search applications, on-site observations and archival data – over a period of nine months from August 2014 to April 2015. Core to our data collection efforts were 16 semi-structured interviews with individuals who were currently or had recently been looking for a job. A criterion-based, purposeful sampling (Patton, 2002) was used for this study in that we selected only participants who were currently or had recently been seeking a job and we tried to maximize variation by sampling participants from different educational backgrounds, age groups, gender and urban/rural places of residence. As such, we were able to gain insights both from digitally advantaged and digitally disadvantaged individuals. Data collected through the interviews with job-seekers was triangulated and enhanced by interviews with corporate recruiters and employment agents at the German Federal Employment Agency (GFEA). In total, we collected 182 pages of field notes which we subsequently evaluated using a semi-explorative content analysis.

#### **4.3 Key findings**

The interviews revealed that the factors that lead to engagement with, or disengagement from, online job search applications differ significantly between the digitally advantaged and disadvantaged. Individuals considering whether to engage or disengage with an application typically pass through a cognitive process that starts with awareness of the salient application, an appraisal of the application as a perceived opportunity or non-opportunity, and an evaluation of the extent to which the individual can control and purposively use the application (Figure 4). Factors such as individual disposition (e.g. motivation), digital skills and social support can affect this process. These factors can vary starkly between digitally advantaged and disadvantaged users and influence the pathway to engagement or disengagement (refer to Figure 5 for a summary).



**Figure 4. Process of (dis-)engagement with Internet applications**

The key factors that result in an involuntary exit by exclusion for the digitally disadvantaged are a combination of limited online skills and often inadequate social support. While it may come as no surprise that skills are an issue for the digitally disadvantaged, a closer look is worthwhile as our observations suggest that not medium-related skills (how to operate and navigate across websites) are the issue, but rather content-related skills related to using an application in an effective, goal-oriented manner. Specifically, the digitally disadvantaged struggled with tasks such as defining meaningful search queries for jobs, filtering and evaluating results, and coping with the perceived complexity of searching for jobs online. Many felt easily confused and overloaded, which led to frustration and disengagement despite the fact that they would have liked to use the application. This is what we term “exit by exclusion” – the case that digitally disadvantaged users perceive an application to be relevant and useful, but lack the skills and control to use it meaningfully.

Social support – or “social capital” – can play a vital role in preventing this critical outcome. Social capital denotes the support an individual can draw from their social network – from family, friends, colleagues, but also from institutions. In the context of job search, these may include secondary or tertiary educational institutions, state institutions such as the GFEA, as well as private or non-profit support organizations that aim to facilitate the job search. We find strong indications that for the digitally disadvantaged social capital has a game-changing impact at all stages of the process leading to engagement. Social capital can trigger awareness for job search applications and influence the consideration set of applications an individual

perceives as useful. Most importantly however, social capital can have a transformative effect on an individual's perceived ability to control an application. It can compensate for an individual's limited skills or self-efficacy by giving advice, teaching and constituting a (theoretical) fallback option for support, thereby translating a feeling of low control to high control and constituting the difference between disengagement and engagement. Digitally disadvantaged individuals profit immensely from having digitally advantaged referents in their support network whom they can draw on for help. Unfortunately, the tendency for social networks to be homogeneous often limits the potential support the digitally disadvantaged can draw from family and friends. This highlights the importance of social institutional capital as a means to overcome this barrier and as a source of critical impulses in cases where individuals' private networks reach their limits. However, a word of caution is appropriate, as misdirected institutional support can prove dysfunctional. Rather than trying to facilitate online job search by taking over tasks for digitally disadvantaged individuals – thereby promoting dependency – institutions should focus on capability building and enabling individuals to act independently online.

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<b>Digitally disadvantaged users</b>	<b>Digitally advantaged users</b>
<ul style="list-style-type: none"><li>▪ Limited awareness of salient applications and functionalities</li><li>▪ Low content-related skills (and self-efficacy) as a critical barrier to use</li><li>▪ Largely homogenous social network that can offer only limited support</li><li>▪ High reliance on institutional support (where available)</li><li>▪ High risk of exit by exclusion due to low control of internet application</li></ul>	<ul style="list-style-type: none"><li>▪ Perceived usefulness and navigability of user interface key to engagement</li><li>▪ Low reliance on social network and institutional support</li><li>▪ Skills rarely a limiting factor</li><li>▪ Satisfactory outcome of engagement critical for positive re-appraisal and continued use</li></ul>

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**Figure 5. Typical user characteristics according to digital proficiency**

## **5. Bridging the gap – what needs to happen?**

The question that emerges is how to bridge the existing digital inequality gap. The issue has garnered much public and political scrutiny, particularly in the early 2000s, and a large number of government initiatives have sprung up as a result. In Germany, Internet access is even legally enshrined as a basic right since 2013 due to its central importance as a part of life. Yet often these initiatives are misdirected. Many federal and municipal initiatives are designed to remove

economic barriers and focus on providing low-cost or free high-speed Internet access despite the fact that penetration rates in developed countries are close to saturation and few structural differences (apart from old age) remain in terms of access. As we have seen, however, merely having access to digital technologies does not ensure that individuals are able to effectively use and leverage these digital technologies. Here, skills and social capital play a decisive role. Initiatives aiming to successfully bridge the gap must place a much stronger focus on nurturing effective use among the digitally disadvantaged and providing the appropriate support structures to that end. In the following, we identify a number of key insights for initiative success from our case study and summarize them in Figure 6.

- ***Embedded institutional support structures:*** Institutionalized support structures are key to helping the digitally disadvantaged overcome the limitations of homogeneous social networks and the ensuing structural deficits. Institutional support can act on many levels. At a federal or state level, government initiatives should focus on firmly anchoring digital education in primary and secondary school curricula to address digital inequality at its roots. This entails three main aspects: a) structurally embed digital education in teaching plans across subjects and ages with the aim to not just learn about digital technology, but also learn with it; b) train-the-trainer: provide teachers with the necessary training and offer on-the-job, continued education; and c) ensure schools have access to the necessary infrastructure (hard- and software, digital learning aids, administration and support) required to disseminate the knowledge. Municipal and community-based support structures, in turn, should target the specific local needs of their populace. Public libraries and community learning centers, for instance, already serve as important digital access points for the digitally disadvantaged and should be activated to provide free or low-cost public trainings and targeted seminars. Where government-led initiatives are lacking, of course, non-profit organizations may take their place.
- ***Focus on skill-building and enablement:*** Initiatives directed at bridging digital inequality should focus on targeted skill-building in order to empower the digitally disadvantaged. Targeted skill-building will need to differentiate between formal, operational skills and content-related, strategic skills that entail the requisite capabilities to use digital technologies effectively and independently. While the former are easier to teach and thus subject of most trainings, they are generally not the critical issue. Formal curricula and digital learning aids could support the wider implementation of content-related strategic skills. Trainings may benefit by drawing inspiration from consumer awareness programs which aim to enable

individuals to evaluate given information, create an awareness for potential upsides and risks, and empower smart decision making. All these “soft” capabilities translate well into the digital context.

- **Application-oriented implementation:** The mechanism through which skill-building initiatives are likely to be most effective is through application-oriented implementation. The key is to bundle digital skills trainings with specific applications that are relevant to the digitally disadvantaged, such as online job search, online education, and e-government services. By doing so, the outcomes of digital education become immediately tangible for the digitally disadvantaged as they learn how to leverage digital tools for specific tasks. Application-oriented initiatives also enable a more cost-efficient and effective support structure founded on a selective needs-basis.
- **Targeted initiatives:** The digitally disadvantaged are often lumped together into one pot with digital initiatives trying to cater to all in the same manner. In reality, the digitally disadvantaged vary significantly in terms of underlying structural deficits (e.g. education, income, age, etc.) and (digital) needs. Initiatives aiming to bridge the digital inequality gap need to account for these different user groups and provide targeted support measures. This will allow structural barriers to be addressed more directly and at the same time ensure that specific digital skills are provided where they are most needed and valued.

<b>Embedded institutional support structures</b>	<ul style="list-style-type: none"> <li>▪ Embed digital education in teaching plan – learning about and with digital technology</li> <li>▪ Train-the-Trainer – on the job, continued online education for teachers</li> <li>▪ Provide necessary infrastructure to schools (hard- and software) to support teaching</li> <li>▪ Leverage municipal and community institutions to provide free or low-cost digital training</li> </ul>
<b>Focus on skill-building and enablement</b>	<ul style="list-style-type: none"> <li>▪ Invest in skill-building – differentiate between formal and strategic skills</li> <li>▪ Target enablement – empower the trainee through experience and learning</li> <li>▪ Reduce barriers to initial and continued use – encourage own digital engagement from day one but offer assistance as a fallback option</li> </ul>
<b>Application-oriented implementation</b>	<ul style="list-style-type: none"> <li>▪ Bundle functional skill trainings with relevant online applications – e.g. offer digital trainings that target job search, online education, or e-health applications</li> <li>▪ Use training format not just to learn, but to create – challenge trainees to apply learnings directly within the context of the training</li> </ul>
<b>Targeted initiatives</b>	<ul style="list-style-type: none"> <li>▪ Segment and target users based on structural deficits and/or digital needs in order to increase motivation, acceptance, and relevance for the participants</li> <li>▪ Offer modular trainings to allow tailored development programs to be devised, such as for technically well-versed users who only struggle with certain skills or certain applications</li> </ul>

**Figure 6. Key insights on designing initiatives to bridge digital inequality**

## **6. Conclusion**

The phenomenon of digital inequality has evolved over time, yet remains a salient and important issue today. Many structural barriers continue to exist which influence how individuals use digital technologies and to what extent they are able to benefit from them. As digital technologies become ever more prevalent in our daily lives and increasingly substitute offline alternatives, the socio-economic repercussions of not being able to properly engage with these technologies become more severe. In domains such as employment and education, the benefits of digital technologies – and the consequences of digital inequality – are most salient. Initiatives aiming to bridge the digital inequality gap should focus on institutional support structures, skill-building and enablement, application-oriented implementation, and targeted, needs-based measures. Digital technology will continue to evolve and only by proactively addressing digital inequality from early on can we ensure that everyone is able to reap the benefits of the digital revolution.

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## **Concluding remarks**

This thesis set out to deepen our understanding on the causes and manifestations of digital inequality through the lens of technology adoption research. To this day, digital inequality remains an important and relevant societal issue. With the rapid proliferation of digital ICT over the last 20 years the nature of the phenomenon may have evolved from an access-based to an appropriation-based issue, yet its significance has not diminished. In fact, as digital technologies increasingly pervade all domains of our lives and progressively substitute offline services, the repercussions of not engaging fully with these technologies are becoming even more apparent. The persistence of digital inequality must be viewed as a call to action to scholars and practitioners alike to understand what is driving differences in digital technology use, what the implications of differential use are in realms such as job search and e-commerce, and how the issue can be addressed.

With this aim in mind, this thesis first developed a theoretical understanding of the concept of social influence, which plays an important role in determining whether and how individuals use a technology. A wide range of conceptualizations exist, yet social influence is still predominantly employed only in its compliance sense, while its internalization and identification effects remain secondary. This narrow focus threatens to undermine the explanatory power of this instrumental construct and limit the research field's understanding of the impact of social influences on technology adoption and use.

Next, a process lens was adopted to explore the underlying mechanisms that drive individuals to disengage from a new technology and may lead to digital exclusion. The findings highlight the importance of social capital, in particular, as well as other capital resources, such as content-related skills, in determining whether an individual attains a favorable outcome, such as engagement, or an unfavorable one, such as disengagement and exit by exclusion.

Building on that, this thesis examined how digital inequality manifests itself in the specific realm of e-commerce, a domain that offers attractive savings potentials for those who are able to effectively leverage them. This is particularly relevant for socio-economically disadvantaged individuals, yet they are the ones who are also most likely to be digitally disadvantaged and to struggle in leveraging these digital opportunities. The findings confirm that despite equal access, significant differences in e-commerce use behavior between the socio-economically advantaged and disadvantaged exist. As such, although Internet applications such as

e-commerce could serve as a potent catalyst to reduce existing socio-economic disparities in both the online and the offline world, this potential is so far not being realized.

The thesis concludes with a practical perspective on the issue of digital inequality. Policy makers seeking to address the issue of digital inequality should in particular focus on ensuring digital inclusion in domains such as education, employment, and health, where digital opportunities are likely to have the greatest impact on socio-economic equality. Moreover, they should make sure that initiatives aimed at reducing digital inequality are embedded within institutional support structures, focus on skill-building and enablement, are implemented in an application-oriented manner, and are targeted towards different user groups.

This thesis provides substantial theoretical and methodological contributions to research on digital inequality and information systems, in particular technology adoption and use. Beyond contributions to academic research, this thesis also develops important insights for public policy makers and managerial practice.

For digital inequality research, the empirical findings presented in this thesis first and foremost underscore that – contrary to claims that the issue would resolve itself by now – digital inequality continues to be a prevalent societal concern, even in countries with widespread Internet access. More specifically, the findings validate that digital inequality has evolved into a second-order effect driven by differences in the way individuals appropriate ICT and the outcomes they achieve, as shown with respect to e-commerce and online job search applications. This thesis contributes to advancing the research field's understanding of the lesser known issues of appropriation and outcome implications by uncovering the underlying mechanisms and factors that influence how individuals engage with ICT. In particular, digital inequality scholars may benefit from the insights that limited awareness, insufficient content-related skills, and a lack of social capital are nowadays much more critical factors for digital exclusion than Internet access and medium-related skills, which have often been the focus of extant research. In addition, this thesis provides insights on how digital inequality manifests itself in fundamental domains of life such as job search and e-commerce, which have so far garnered little specific research attention. In fact, to the best knowledge of the author, it is the first to empirically test and validate the hypothesized e-commerce divide. Furthermore, this thesis illuminates that social capital plays a more instrumental role than commonly portrayed in the context of digital inequality research. It highlights how and under which circumstances social capital can be converted into forms of capital instrumental to technology engagement

and thereby compensate for risk factors that favor disengagement, such as limited awareness and low control. Future digital inequality research should build on these findings to derive how social capital in general, and institutional social capital in particular, may be strategically employed as a means of intervention to prevent disengagement and involuntary digital exclusion.

This thesis also provides substantial contributions to research on information systems and in particular to the field of technology adoption and use. In contrast to most extant research in this field, which is variance-based, this thesis adopts a process perspective to account for the dynamic nature of user (dis-)engagement, yielding a more multi-faceted understanding of the mechanisms of technology use and non-use and the ensuing outcomes. In so doing, it responds to calls to investigate alternative theoretical perspectives on technology acceptance in order to broaden the field's understanding towards a wider constellation of behavioral responses (Abraham et al., 2013; Schwarz & Chin, 2007; Venkatesh et al., 2007). It also extends the field's understanding of the role individual resources, such as cultural and social capital, can play at different stages of the engagement process and how they can contribute either to continued use or promote disengagement. Furthermore, this thesis also develops a novel and more holistic conceptualization of e-commerce use that goes beyond the notion of a simple purchase and accounts for the context in which a transaction takes place, which is seldom one-dimensional. The advantages of such an expanded conceptualization of use lie in a more faithful representation of usage activities, thereby contributing to a more nuanced and differentiated understanding of e-commerce, particularly with regard to economic utility-enhancing activities. Moreover, by drawing on sociology communication research this thesis also introduces a new, more differentiated perspective on Internet skills into the technology adoption and use discussion. A differentiated view on skills is necessary to understand how exactly skills foster or impede technology use. The findings of this thesis underscore the relevance of this view by revealing that medium-related skills, which have often been highlighted as one of the most important barriers to technology use, are in fact widely present, while content-related skills, needed to effectively evaluate and navigate online options, seem to be a critical inhibiting factor. Finally, this thesis also contributes to advancing our theoretical understanding of social influence on technology adoption by reconciling its manifold conceptualizations and developing an integrated framework that provides promising vantage points for future research.

Above and beyond contributions to theory, this thesis also has two major methodological contributions. The first is the introduction of clickstream data as an empirical basis for studying technology use and digital inequality. A prevalent methodological concern of research in these domains is common method bias. The use of clickstream data allows this methodological limitation to be overcome since clickstream tracks actual use over a sustained period of time rather than intended behavior at a single moment in time. It thus provides a far richer and more accurate depiction of how individuals are using digital technologies than typical survey-based inquiries and is uniquely suited to uncover granular differences in patterns of use across large-scale samples. The second methodological contribution lies in the use of a qualitative research approach to uncover the underlying mechanisms that influence the observed differences in use patterns. Human behavioral responses towards technology use are multifaceted and dynamic in nature, and an explorative, interview-based approach is able to capture the diversity of these responses in greater depth and richness than traditional, survey-based research. In so doing, this thesis also specifically responds to calls to broaden our understanding towards a wider constellation of behavioral responses (Abraham, Boudreau, Junglas, & Watson, 2013) and more in-depth qualitative research (Selwyn, 2003; Venkatesh, Brown, & Bala, 2013).

In terms of practical contributions, this thesis first and foremost serves to inform public policy makers in devising targeted policy interventions aimed at fostering digital inclusion. Most importantly, policy makers should be conscious of the fact that access-based initiatives alone do not suffice in addressing second-order digital inequality. Rather, they need to place a much stronger focus on nurturing effective use among the digitally disadvantaged and providing the appropriate support structures to that end. Here, institutions at the federal, state, and municipal level, such as schools, government agencies, and community centers, play a central role in helping the digitally disadvantaged overcome the limitations of homogeneous social networks and the ensuing structural deficits. Moreover, policy makers should make sure that the initiatives they devise specifically focus on skill-building and enablement, are application-oriented, and accessible on a selective needs-basis.

In addition, the findings outlined in this thesis also have practical implications for managerial practice. Online and multichannel businesses can benefit by being aware of digital inequality and developing strategies to adequately cater to user groups such as the digitally disadvantaged. By effectively targeting these currently alienated user groups, businesses can potentially expand their customer base and generate additional revenue. Moreover, an understanding of how individuals appraise and engage with Internet applications can help businesses streamline

their online portals towards facilitating use and removing critical barriers and drop-out points. In doing so, online businesses may benefit not only from new customers but also higher conversion rates and a higher customer lifetime value.

In conclusion, digital inequality remains a prevalent societal concern that will continue to evolve as digital technologies increasingly pervade all domains of life. This thesis has sought to advance our understanding of the causes and manifestations of digital inequality, yet significant potential for future research remains. I hope that this thesis serves as a helpful foundation for other scholars interested in digital inequality and technology use to build on.

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**[Supplement A]**

**Second-order digital inequality:**

**The case of e-commerce (as published in The  
Proceedings of the ICIS 2014)**

# Second-Order Digital Inequality: The Case of E-Commerce

*Completed Research Paper*

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## **Abstract**

*“Second-order digital inequality” describes that certain individuals profit less from digital opportunities not only due to limited access but also due to limited abilities to use information and communication technologies (ICT). This study extends research on second-order digital inequality to the realm of e-commerce. We introduce a novel conceptualization of effective, potentially beneficial, e-commerce use that encompasses two dimensions: (1) the diversity of e-commerce platforms used by an individual; (2) the degree to which an individual uses supporting e-commerce features. Building on technology acceptance theory and social psychology, we argue that socio-economically disadvantaged individuals are less likely to use e-commerce effectively than socio-economically advantaged individuals. We empirically test our hypotheses on clickstream data that tracks the online behavior of 2819 US e-commerce users for six months. Our findings reveal that, despite equal access, the socio-economically advantaged use e-commerce more effectively regarding both dimensions. Implications for research and practice are discussed.*

**Keywords:** Digital inequality, e-commerce, digital divide, e-commerce platforms, e-commerce functionalities, technology acceptance

## Introduction

Ever since its inception, scholars have discussed the impact of the Internet on society (DiMaggio et al., 2001). Proponents of the Internet argued it could provide people access to new ways of creating value and thus foster societal wealth and wellbeing (Hargittai, 1999; Madon, 2000). Some authors even suggested that new Internet-based technologies would level the playing field between societal strata and reduce social inequality (Anderson et al., 1995). In contrast, others contended that rather than reducing economic disparities within and across societies, the Internet could in fact lead to “increasing inequalities, improving the prospects of those who are already in privileged positions while denying opportunities for advancement to the underprivileged” (Hargittai, 2003).

Within the debate on the social ramifications of the Internet, the phenomenon of “digital inequality” has received substantial attention (Hargittai & Hinnant, 2008; Hsieh et al., 2008; Kvasny & Keil, 2006; Riggins & Dewan, 2005). Digital inequality refers to the difference between individuals regarding their access to, and ability to use, information and communication technologies (ICT) (DiMaggio et al., 2004). Early studies observed so called “first-order” digital inequality by showing that the socio-economically disadvantaged typically have less access to ICT than their advantaged peers (DiMaggio et al., 2001; Katz & Rice, 2002). More recently, scholars have turned their attention to “second-order” digital inequality by noting that individuals also differ with regard to the way they *use* ICT depending on their socio-economic status (DiMaggio & Hargittai, 2001). Scholars have explored digital inequality, focusing on central and potentially beneficial Internet uses such as information search (van Deursen, 2012), e-government participation (Bélanger & Carter, 2009) and capital-enhancing websites (Zillien & Hargittai, 2009). They cautioned that, due to digital inequality, less privileged individuals may be less able to profit from the opportunities the Internet has to offer (Mossberger et al., 2003).

Recently, e-commerce has emerged as an additional area of opportunity creation within the digital inequality discussion. With worldwide online sales exceeding \$1 trillion (eMarketer 2013), e-commerce captures a substantial share of the global business. More importantly, a wide range of e-commerce platform formats and features have evolved that help individuals to optimize the economic outcome of their purchases. For instance, e-coupons, price comparisons, or auctions are means by which individuals can shop cheaper than in the brick-and-mortar world. In other words, users who are able to shop more effectively by leveraging e-commerce functionalities potentially generate a substantial economic surplus (Dewan and Riggins 2005). Thus, e-commerce might be particularly beneficial for the socio-economically disadvantaged.

Despite the potential benefits of e-commerce for online shoppers, almost no scholarly attention has so far been devoted to digital inequality in the context of e-commerce. Prior research (Akhter, 2003; P. E. N. Howard et al., 2001; Zillien & Hargittai, 2009) suggests that, contrary to homo economicus expectations, those with the least economic resources are less likely to fully leverage the breadth of opportunities available to realize savings when shopping online. These findings imply that economic inequality in the “offline” world might be further perpetuated in the “online” universe. However, extant digital inequality research has mainly focused on selective aspects of e-commerce and there has been little consideration of the general role of e-commerce as a potential amplifier or compensator of inequality. So far there is only little empirical evidence on the existence of digital inequality within e-commerce and only a limited theoretical conceptualization of what actually constitutes inequality with regard to e-commerce use. In this vein, scholars called out for research that better conceptualizes and studies digital inequality in the context of e-commerce (Riggins & Dewan, 2005).

We seek to address this research gap by exploring how individuals vary in how they use e-commerce as a function of their socio-economic status and, in turn, whether e-commerce amplifies or attenuates digital inequality. We focus specifically on the influence of an individual’s socio-economic status on two aspects of e-commerce use that promise economic gains, namely (1) the extent to which an individual is able to leverage the *diversity of e-commerce platforms* available within the product purchasing step (e.g., general retailers, daily deals, flash sales); and (2) the degree to which an individual employs *supporting features* such as e-coupons and price comparisons within the information search step to further benefit from e-commerce. We draw on technology acceptance theory and social psychology to hypothesize that socio-economically disadvantaged online shoppers tend to shop less diversely and will be less likely to make use of supporting e-commerce features. We test these hypotheses on a unique set of clickstream data which tracks the online behavior of 2,819 US participants for 6 months in 2012.

Our study most importantly contributes to digital inequality research by highlighting that second-order digital inequality is a prevalent societal issue and persists within the context of e-commerce. We further add to the broader context of information systems research by introducing an innovative

conceptualization and operationalization of e-commerce system use that may be extended to other technologies. Moreover, using clickstream data as empirical basis of our research represents a novel approach to investigate technology acceptance based on actual rather than intended behavior. Finally, our research has important implications for public policy and managerial practice. Understanding how socio-economic status impacts e-commerce use may influence policy making with regard to digital skills, ICT education and consumer protection and might help businesses to effectively target different societal groups.

## **Theory and Hypotheses**

### ***Digital Inequality: The Perpetuation of Socio-economic Status Online***

“Digital inequality” denotes the difference between individuals in terms of their access to, and the ability to use, ICT which in turn restrains them from realizing opportunities offered through those technologies (DiMaggio et al., 2004). While digital inequality has been observed with regard to various demographic dimensions such as gender, race, and age (Chaudhuri et al., 2005; Rice & Katz, 2003), the phenomenon has been particularly highlighted in the context of socio-economic differences between individuals as reflected in their income and education (J.-Y. Jung et al., 2001). Mossberger et al. (2003), for instance, found that individuals with lower income and education are restricted in their job prospects due to their relative lack of access and skills to use ICT in a working environment.

Digital inequality constitutes a complex and multi-faceted societal challenge on the global level as well as within national societies (OECD, 2013; UN, 2013). Researchers have argued that digital inequality is a perpetuation of underlying social disparities in the “real” world (Kvasny & Keil, 2006; Norris, 2001; Warschauer, 2003). It has been cautioned that, comparable to the so-called “Matthew effect” (Merton, 1973), peoples’ initial advantages in technology access may translate into increasing relative returns over time, thereby further widening the gap between the more and the less privileged parts of society.

Scholars have devoted increasing attention to digital inequality and its underlying mechanisms. Earlier research focused on the first-level “digital divide” (DiMaggio & Hargittai, 2001) which denotes differences in people’s access to ICT and its sociological implications such as exclusion from online education (Katz & Rice, 2002). More recent studies noted that access to Internet is losing importance, with broadband penetration in developed countries almost at saturation levels (e.g., 80% in 2012 in the U.S.; OECD 2013). Correspondingly, recent research seeks to shed light on the so-called “second-level” digital inequality (Hargittai 2002: p.1): rather than studying *whether* individuals use the Internet or not, the debate now focuses on exploring differences in *how* people use the Internet to create opportunities for themselves. Mossberger et al. (2003) suggested three different manifestations of digital inequality: first, a skills divide related to the individual ability to handle computers and the Internet and to get access to information; second, an economic opportunity divide resulting from people’s inability to participate in Internet-based education, training, and employment opportunities; and third, a democratic divide due to the inability to engage in e-government. In this vein, digital inequality scholars have explored aspects such as general Internet skills (Hargittai, 2010) and the adoption of e-government (e.g., Helbig et al. 2009). For instance, van Deursen and van Dijk (2010) studied Internet skills in the Dutch population and observed that lower education predicted lower Internet skills. In our study, we focus on one aspect related to ICT, which has also been proposed to be affected by, and to affect, digital inequality (Riggins & Dewan, 2005): the use of e-commerce.

### **E-commerce and the Potential Economic Benefits of Platform Use Diversity and Supporting E-commerce Features**

E-commerce in the business-to-consumer context has been defined as the trade of products and services online (Olson & Olson, 2000). The U.S. Department of Commerce (2014) estimates that, in 2013, U.S. citizens spent US\$ 263 billion for products and services online and that online sales will reach US\$ 370 billion by 2017 (Inc, 2013). In 2014 alone, e-commerce sales are expected to increase by an additional 14% as opposed to sales in 2013 (Centre for Retail Research 2014).

Given the growing importance of e-commerce, scholars in information science have studied various aspects of people’s use of e-commerce. For instance, behavioral research in e-commerce illuminates which factors motivate individuals to engage in online shopping in general (Gefen et al., 2003; Gefen & Straub, 2000; Pavlou & Fygenson, 2006). Other researchers have investigated specific e-commerce functions such as auctions and e-coupons (Bosnjak, Obermeier, & Tuten, 2006; K. Jung & Lee, 2010).

In the context of our study it is important to define what actually constitutes effective —i.e., potentially beneficial from an economic point of view—e-commerce use. Buyer decision making models break down the purchasing process into a number of steps (Engel et al. 1973), of which information search and the product purchasing decision are considered to be the most important within the online context (Gefen and Straub 2000). When considering the product purchasing step, the continuous evolution of the e-commerce landscape over the last decade needs to be taken into account. Today, consumers can choose among a diverse variety of formats and vendors from which to buy a product. For instance, the rapid proliferation of innovative formats such as auctions, daily deal or flash sale sites provide consumers with an increasing range of alternatives to traditional online retailers such as Amazon.com and the opportunity to save money by finding the best deal. Likewise, in the information search step consumers can choose between different e-commerce features to optimize prices (in addition to getting general product information), predominantly through price comparisons and e-coupons. Consequently, a conceptualization of effective e-commerce use should account for the heterogeneous information search and product purchase options available that offer individuals the potential to achieve economic benefits and thus go beyond the traditional use concept of a simple transaction made online.

In this study, we focus on two specific aspects of e-commerce use, both of which are particularly likely to create economic benefits for users in either the information search or the product purchasing phase (1) the extent to which an individual is able to leverage the diversity of e-commerce platforms available within the product purchasing step (e.g., general retailers, daily deals, flash sales); and (2) the degree to which an individual employs supporting features such as e-coupons and price comparisons within the information search step to further benefit from e-commerce. We define “*e-commerce platform use diversity*” as the variety of e-commerce platforms an individual uses when shopping online. This definition entails two particular aspects. First, it accounts for the general degree to which an individual makes use of different e-commerce websites and platforms when shopping online. Online shoppers can access a wide a range of e-commerce platforms, for example general retailers such as Amazon.com, specialized retailers such as Zappos.com, and brand shops such as Nike.com. Research within offline retail has shown that a larger number and variety of store visits per week leads to an economic advantage (Carlson & Gieseke, 1983): those individuals shopping for groceries who make more trips to different stores achieve lower prices on average because of price dispersion between stores. Similar patterns of price dispersion can be observed online (Ba et al., 2012). Correspondingly, online shoppers who selectively switch between e-commerce websites and leverage the breadth of platforms available are more likely to achieve economic gains.

A second particular aspect entailed in the definition of platform use diversity is the users’ participation in ‘alternative’ e-commerce formats such as auctions (e.g. Ebay.com), flash sales (e.g. Gilt.com), and daily deal sites (e.g. Groupon.com). Prior research shows that especially alternative e-commerce formats offer significant cost savings for users. For instance, Bapna et al. (2008) estimate that the consumer surplus from auctions on Ebay.com exceeded US\$ 7 billion in 2003. Similarly, daily deal and flash sale websites offer heavily discounted deals for a limited time (Boon, 2013; Martinez & Kim, 2012), improving users’ odds to achieve lower prices than in other sales channels.

We define “*supporting e-commerce features use*” as an individual’s use of price comparisons and e-coupons in connection with an online transaction. Price comparison websites such as Shopping.com or Bizrate.com increase consumer power by creating price transparency and by offering additional product information. Research has shown that the potential savings resulting from the use of price comparison websites can be significant (Rezabakhsh et al., 2006). For instance, Baye et al. (2004) examined four million prices for 1000 consumer electronics products and found that, despite increased transparency, price dispersion ranged from an average of 3.5 percent up to 23 percent. Moreover, consumers can achieve additional savings by leveraging websites that offer free promotional e-coupons such as Retailmenot.com or Coupons.com. E-coupons are digital codes which entail a price reduction for a given product or website (K. Jung & Lee, 2010). Thus, using e-coupons enables users to capture a higher economic gain per transaction on a given platform.

### **Digital Inequality in E-commerce Use**

Extant studies have repeatedly called for research on digital inequality in the context of different ICT use applications (DiMaggio et al., 2004, 2001; Hargittai & Hinnant, 2008; Zillien & Hargittai, 2009) and e-commerce in particular (Akhter, 2003; D. L. Hoffman, Novak, & Schlosser, 2006). Specifically, Dewan and Riggins (2005) introduced the notion of an “e-commerce divide,” which they defined as “certain people’s inability to make use of more advanced e-commerce online functionalities and services” (2005: p. 318). They argue that even in the case of equal Internet access, socio-economically

disadvantaged individuals might be less able to seize the multiple opportunities to achieve economic gains that are offered by e-commerce.

The notion of an “e-commerce divide” carries a number of intriguing theoretical implications. First, such a divide contradicts assumptions about rational behavior, opportunity cost and the decreasing marginal value of money. Under such assumptions, one would expect the motivation to save cost through e-commerce to be strongest for those individuals with the least financial resources and that those who earn the least would incur less opportunity cost when investing time online. Ultimately, this would prevent the emergence of an e-commerce divide. Second, the existence of an e-commerce divide seems counterintuitive since e-commerce theoretically carries the potential to reduce—rather than reinforce—disparities regarding consumption possibilities in the offline world (Anderson et al., 1995). While, in the brick-and-mortar universe, product availability, access, and pricing are highly dependent on the consumer’s place of residence and typically favor those consumers who live in well developed areas, in the online world the product offering and prices are principally identical for everybody. In addition, the costs to search for products and prices on the Internet are lower compared to the offline world, for instance due to automated price comparisons. In the offline world, information search is costly, which might prevent those from lower income classes to extensively search for the best product at the best price. Altogether, the notion of an “e-commerce divide” contradicts *homo economicus* assumptions about consumer behavior and the theoretical “equalizing power” of e-commerce. Thus, it seems particularly interesting to explore whether and why e-commerce eventually attenuates or fortifies digital inequality.

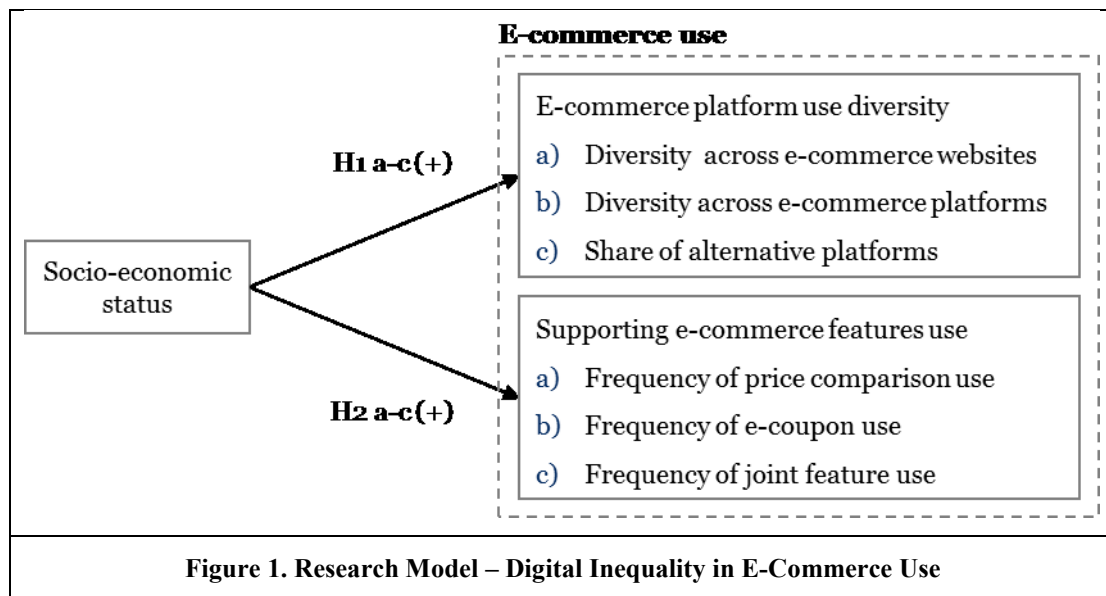
To build hypotheses on the relation between an individual’s socio-economic status and his or her tendency to use a diverse set of e-commerce platforms and supporting e-commerce features, we draw on Davis’ (1989) technology acceptance model (TAM). TAM is a widely accepted model in information systems research (Benbasat & Barki, 2007; Taylor & Todd, 1995c; Venkatesh & Davis, 2000; Venkatesh et al., 2003) and has been extended to robustly predict various facets of consumers’ use behavior in the context of e-commerce (Gefen & Straub, 2000; Koufaris, 2002; Pavlou, 2003) such as online auctions (Stern et al., 2008) and e-coupons (Kang et al., 2006). TAM originally predicts an individual’s intention to use new technologies as a function of two factors (Davis, 1989): perceived ease of use, which describes the subjective degree of effort required to use a technology; and perceived usefulness, which refers to the individual’s perception of the utilitarian gains that can be derived from using a technology. In our study, we will use the equivalent term of utilitarian motivation in lieu of perceived usefulness to denote an individual’s motivational disposition (see Hsieh et al., 2008).

In line with prior e-commerce research (e.g., Ahn et al. 2007; Pavlou 2003), we apply an extended, context-specific TAM. In their quest to continuously refine the TAM and adapt it to the context of e-commerce, scholars have dedicated particular attention to perceived risk as an additional precursor of an individual’s e-commerce use (Gefen et al., 2008). The individual’s perception of risk is quintessential when studying e-commerce use because the consumer and the Internet store are physically separated and therefore online transactions have an inherently impersonal nature (Bhatnagar & Ghose, 2004; D. Kim & Benbasat, 2003; Pavlou, 2003). Glover and Benbasat (2010) describe the perceived risk of online shopping as an aggregate of an individual’s subjective assessment of three dimension of risk: first, the risk of information misuse, e.g. abuse of personal or financial data; second, the risk related to product benefits, e.g., the risk that a product will not arrive; and third, the risk of functionality inefficiency, e.g. that returning a product will be too difficult.

Further, scholars introduced the construct of hedonic motivation as a complementing element to increase the predictive power of TAM in the context of e-commerce (Ahn et al., 2007; Ha & Stoel, 2009). In this context, hedonic motivation is the degree to which an individual can derive enjoyment from online shopping (Childers et al., 2001). In contrast to utilitarian motivation, which describes the outcome driven extrinsic motivational factors for using a technology, hedonic motivation refers to the intrinsic motivation reinforced only by “the process of performing the activity per se” (Davis et al. 1992: p.112). Researchers investigating online consumer behavior have shown that hedonic aspects of online shopping are different from those in the brick-and-mortar universe, but equally important. For instance, sensory stimulation offered through a website, the playfulness of a website, and the ability to share e-commerce experiences with others improve the odds that consumers perceive online shopping as more enjoyable and show more intention to shop online (e.g., Ahn et al. 2007; Childers et al. 2001; Lin et al. 2005; Moon and Kim 2001).

The central idea of our study is that, because of their socio-economic status, individuals tend to differ in their use of e-commerce. The socio-economically disadvantaged will differ from their advantaged

peers in terms of their perceived ease use, i.e. the degree to which they are affected by e-commerce complexity. Moreover, less privileged individuals are likely to differ from the more privileged in their motivational dispositions, i.e., regarding the relative importance of hedonic and utilitarian stimuli. Lastly, they are likely to be distinct regarding the degree to which they perceive e-commerce as risky. We argue that these dispositions, in turn, lead to status-induced differences in how individuals behave regarding their e-commerce platform use diversity and their use of supporting e-commerce features. . The general logic of our theorizing is illustrated in Table 1 by using TAM constructs to link socio-economic status and e-commerce use. We display our research model in Figure 1 and describe it in the following passages.



### Digital Inequality Regarding E-commerce Platform Use Diversity

Three rationales lead us to argue that socio-economic status is linked to platform use diversity. First, the increased complexity of using multiple e-commerce platforms is likely to affect the perceived ease of use of the socio-economically advantaged individuals to a lesser degree than the perceived ease of use of the socio-economically disadvantaged. Technology complexity has long been identified as a major barrier to ICT use, including e-commerce (Rice & Katz, 2003). However, social psychology suggests that the socio-economical differences cause people to vary in how they perceive complexity: privileged individuals typically have better access to skills and techniques that allow them to cope more easily and flexibly with challenges (Fan & Eaton, 2001), which is one reason why they are less affected by stress creating factors (L. W. Hoffman, 2003), including environmental complexity. Relatedly, scholars studying individual digital skills found a divide between socio-economic classes regarding the skills required to accomplish certain Internet tasks. For instance, van Deursen (2012) uncovered that individuals with a lower level of education were less able to access health information on the Internet. In this vein, we argue that the perceived ease of use for using a diverse set of e-commerce platforms is likely to be higher for the socio-economically advantaged given their general disposition to cope more flexibly with complexity as well as their higher level of education and Internet skills. Therefore, we anticipate that the socio-economically disadvantaged are likely to shop less diverse than the socio-economically advantaged.

TAM construct	Definition	Relative importance of construct depending on socio-economic status	Support for identified relative importance from existing literature	Illustration of specific TAM construct influence on e-commerce use (examples)	
				Platform use diversity	Supporting e-commerce features
Perceived ease of use (PEOU)	Subjective degree of effort required to shop online (Davis, 1989)	Relatively <i>higher</i> for the <i>socio-economic advantaged</i>	Van Deursen (2012), Fan and Eaton (2001), Hoffman (2003), Rice and Katz (2003)	(+) Requires PEOU to manage e.g. multiple interface complexity	(+) Requires PEOU, e.g. evaluate price comparison search results
Utilitarian motivation	Individual perception of gains that can be derived from shopping online (Davis, 1989)	Relatively <i>higher</i> for the <i>socio-economic advantaged</i>	Bonfadelli (2002), van Deursen and van Dijk (2010), Hargittai and Hinnant (2008), Norris (2001)	(+) Provides utilitarian benefit of cost savings, e.g. through using auctions or daily deals	(+) Provides utilitarian benefit of cost savings, e.g. thorough price transparency
Hedonic motivation	Degree to which an individual can derive enjoyment from online shopping (Childers et al., 2001)	Relatively <i>higher</i> for the <i>socio-economic disadvantaged</i>	Aneshensel (1992), Hsieh et al. (2008), Mathwick et al. (2001), Parker and Endler (1996)	(+) Provides hedonic benefits like e.g. novelty, thrill and feeling of escaping reality	(+) Hedonic benefits limited, e.g. to the joy of searching
Perceived Risk	Individual assessment of the risks associated with online shopping related to information misuse, product benefits and functionality inefficiency (Glover & Benbasat, 2010)	Relatively <i>higher</i> for <i>socio-economic disadvantaged</i>	Schechter (2007), McLeod and Kessler (1990), Bhatnagar and Ghose (2004), Shaw (1996)	(-) Increases risk, e.g. through multiple disclosure of personal and financial data	Not applicable

**Table 1. Using TAM constructs to link socio-economic status and e-commerce use**



Second, socio-economic status is likely to influence the motivational dispositions of individuals (Holbrook & Hirschmann, 1982; Holbrook, 1986), in particular their utilitarian and hedonic motivation, which in turn makes the socio-economically disadvantaged less likely to shop on a diverse range of platforms. Findings from digital literacy research suggest that obtaining utilitarian benefits is likely to be relatively more important for the socio-economically advantaged as opposed to their disadvantaged peers. For instance, Hargittai and Hinnant (2008) investigated the Internet use behavior of young adults and found that those with less education and from lower income backgrounds used the web to a lesser degree to read news or gather information on finance, health, politics or products. Further, Bonfadelli (2002) studied the Internet use behavior of more than 1400 individuals and found that those with less formal education used the Internet mostly for entertainment, while those study participants with more education used the Internet rather for informational and serviced-related purposes. Some scholars argue that the better education of the socio-economically advantaged puts them in a better position to assess and acknowledge the usefulness of ICT functionalities (Norris, 2001). Other authors see the relatively lower importance of utilitarian benefits as a consequence of a lack of digital skills required to fully leverage existing utility maximizing opportunities (van Deursen & van Dijk, 2010).

A high level of utilitarian motivation, in turn, positively influences an individual's inclination to shop on a diverse range of e-commerce platforms. Shopping on different platforms provides utilitarian benefits, such as a greater potential to save costs and profit from better product availability as a result of visiting a range of shopping platforms rather than just one. Similarly, the use of alternative platforms such as auctions, daily deals and flash sales offers significant cost savings (Bapna et al. 2008; Boon 2013; Martinez and Kim 2012) and thus provides utilitarian benefits. Given the relatively higher importance of utilitarian benefits for the socio-economically advantaged, they will most likely exhibit more diverse shopping patterns than socio-economically disadvantaged individuals.

Vice-versa, consumer research and social psychology suggest that obtaining hedonic benefits is likely to be relatively more important for the socio-economically disadvantaged than for their more advantaged peers. Less privileged individuals were found to be generally more exposed to stressors (Aneshensel, 1992) and hence more in need of hedonically achieved stress relief, which is, for instance, provided by shopping (Arnold & Reynolds, 2003). Moreover, socio-economically disadvantaged individuals exhibit a greater tendency to cope with life difficulties by escaping into different worlds (Parker & Endler, 1996). This form of social escapism has already been found to be a hedonic motivational driver of online shopping behavior (Y.-K. Kim, 2002; Monsuwé et al., 2004; Overby & Lee, 2006). Internet-based entertainment provides a further opportunity especially for the socio-economic disadvantaged to "get away from it all" (Mathwick et al. 2001: p.44). As such, it is not surprising that earlier work on digital inequality finds that socio-economically disadvantaged individuals are more strongly attracted by hedonic elements of ICT use than their more advantaged peers (Hsieh et al., 2008).

Diverse online shopping patterns may also be driven by hedonic motivation. In particular, hedonic benefits such as novelty (Arnold and Reynolds 2003), a feeling of escaping reality (Mathwick et al. 2001) or thrill in the case of auctions (Turel et al. 2011) may be further augmented through diverse e-commerce use. Consequently, from a hedonic motivation point of view, the socio-economically disadvantaged may be more inclined to shop on a large range of platforms. However, we believe that hedonic motivators are less relevant in the context of our study than utilitarian motivators given that scholars found utilitarian motivation to have a much stronger impact on ICT use than hedonic motivation. Notably, this relationship has been substantiated not only in the case of workplace ICT use (Davis et al. 1992), where it might be expected, but also in the case of a leisure activity such as e-commerce (e.g., Ahn et al., 2007; Childers et al., 2001). These findings reflect that people predominantly use ICT in an instrumental way to achieve a certain outcome, corresponding to utilitarian motivation, rather than for reasons of performing the activity per se, which corresponds to hedonic motivation. So even though shopping on a large range of platforms may convey some hedonic benefits, the utilitarian benefits are expected to be the stronger driver of diverse shopping behavior. As such, socio-economically advantaged individuals, who are more strongly motivated by utilitarian benefits, will most likely exhibit more diverse shopping patterns than their disadvantaged peers who are more strongly motivated by hedonic shopping benefits.

Third, socio-economically disadvantaged individuals are less likely to shop on a large range of platforms since their risk perception of a given e-commerce activity is likely to be relatively higher than those of their advantaged peers. Economists generally postulate that people with higher income are less risk-averse (Schechter, 2007). Additionally, psychologists found that individuals from lower income classes show a more intensive emotional vulnerability with regard to financial losses (McLeod & Kessler, 1990). In the specific context of e-commerce, Bhatnagar and Ghose (2004) segmented consumers based on

their risk and benefit perception of online shopping and found that the perceived product risk as well as the perceived security risk were highest in the lowest income class.

A high level of perceived risk associated with online shopping, in turn, inhibits diverse shopping behavior on multiple platforms. With the transfer of transactions from the offline to the online world, the risk associated with buying a product has undeniably risen and constitutes a major influencing factor on e-commerce behavior (Pavlou, 2003). The required multiple disclosure of private and financial data on different e-commerce sites associated with a diverse shopping behavior further increases the probability of personal data misuse. This might discourage risk-averse individuals from engaging in diverse e-commerce use. This behavior is likely to be reinforced as soon as an individual has built a trust-based relationship with one e-vendor through repeated transactions, making risk-averse individuals even more reluctant to switch to another e-vendor (Gefen, 2002). Given the relatively higher risk perception of online shopping of the socio-economically disadvantaged, they might thus be less inclined to shop on a large range of platforms compared to the socio-economically advantaged.

Based on the differential behavior regarding perceived ease of use, hedonic and utilitarian motivation, and perceived risk, we formally propose:

*H1a-c: The higher an individual's socio-economic status the more diverse will be the individual's transaction behavior when shopping online: (a) in terms of e-commerce websites used, (b) e-commerce platforms used, and (c) share of alternative platforms used.*

### **Digital Inequality Regarding Supporting E-commerce Features Use**

In line with the argumentation above, perceived ease of use and differences in motivational dispositions will lead to differential use of supporting e-commerce features of the socio-economically advantaged and disadvantaged. Perceived risk is assumed to not influence the use of supporting e-commerce features since price comparison and e-coupon websites do not usually require the disclosure of personal data and the use of these features does not constitute a transaction.

Building on findings that perceived ease of use of accepting a technology is relatively lower for the socio-economically disadvantaged, it seems likely that they will experience greater difficulty in using supporting e-commerce features. The use of supporting e-commerce features adds complexity to online shopping. While it is relatively easy for an individual to access price comparison websites, a certain level of information evaluation skills is required to sort out search results and to select a vendor imposing a potential complexity barrier (van Deursen & van Dijk, 2010). In line with traditional coupon research (Levedahl, 1988) we assume that the complexity of searching for e-coupons on a broad variety of websites and testing e-coupon validity constitutes an additional barrier. Building on the argumentation above we argue that due to missing skills and a lower ability to handle complexity, using supporting e-commerce features will be more difficult for the socio-economically disadvantaged.

Given that the socio-economically disadvantaged are also likely to be relatively less motivated by utilitarian benefits, which are important drivers of supporting e-commerce features use, they are likely to use price comparisons and e-coupons less frequently when shopping online. The use of price comparison websites and e-coupons mainly grants utilitarian benefits while hedonic elements are rare. Price comparisons generate utilitarian value through increased price transparency and the potential to save cost (Bock et al., 2007). The use of e-coupons is generally viewed as a means to generate additional savings at the point of sale and thus also mainly exhibits utilitarian shopping benefits (K. Jung & Lee, 2010). For both price comparisons and e-coupons, factors related to hedonic motivation are limited. As theorized above, the socio-economically disadvantaged are relatively less motivated by utilitarian shopping benefits. Thus, we posit the socio-economically disadvantaged to be less motivated to use supporting e-commerce features. Building on the reasoning above, we formally propose:

*H2a-b: The higher an individual's socio-economic status the higher will be the frequency of (a) price comparison use and (b) e-coupon use when shopping online.*

An individual who not only uses either price comparisons or e-coupons but both features conjointly is likely to achieve even higher gains but at the same time will be faced with higher task complexity. Thus:

*H2c: The higher an individual's socio-economic status the higher will be the frequency of joint price comparison and e-coupon use when shopping online.*

## **Methodology**

### ***Data Sample***

We test our hypotheses on a unique set of clickstream data courtesy of comScore. Clickstream data represents a record of an individual's online activities. It tracks the user's navigation path online, collecting information, for example, on the websites the user visits, the actions carried out on each site as well as e-commerce transaction details such as domain name, product and price. In contrast to site-centric data, which only assimilates information for a given website, syndicated clickstream data is "user-centric" (Padmanabhan et al., 2001), as it chronicles the online activities of users across multiple websites.

Clickstream data is a particularly powerful empirical basis for studying facets of Internet use. It is frequently applied in the field of online marketing in order to evaluate browsing behavior, effectiveness of online advertising and online shopping patterns (Bucklin & Sismeiro, 2009). With regard to the latter, the focus has largely been on predicting purchase conversion, understanding factors driving successful transactions and investigating auction pricing mechanisms (Moe, 2006; Park & Bradlow, 2005).

Using clickstream data as an empirical basis has several key advantages. First, it avoids typical weaknesses of cross sectional data such as self-report bias and common rater effects (Podsakoff et al., 2003) by tracking actual behavior. Second, a clickstream dataset typically covers a period of several months. The longitudinal nature of the data means that the risk of a sustained behavioral bias by the user is minimal. Third, user-centric clickstream data in particular encompasses a very large and detailed set of information that would be difficult to aggregate using survey-based measures. For the purpose of our study, which attempts to understand e-commerce use in a more in-depth and nuanced manner, clickstream data provides the level of detail needed to accurately capture use.

Our dataset comprises 19958 Internet users from 10000 households in the US whose Internet activities were tracked for a period of 6 months from May to October 2012. Participants are part of an opt-in comScore consumer sample which is compiled using industry standard methodologies such as random digit dial (RDD) recruitment and through membership incentives. In order to normalize self-selection bias in the opt-in sample, comScore employs a technique called "iterative proportional fitting". In this process they use an enumeration survey and calibration panel sample with participants only recruited via (Cook and Pettit, 2009). Obtained measures are used to calculate a weighting scheme for the opt-in panel in order to ensure population representativeness and normalize the main sources of self-selection bias such as proportionally attracting more heavy users (comScore, 2014).

In order to ensure sample validity, a number of restrictions were applied. Transactional data observations were limited to four product categories: apparel & accessories, consumer electronics, home supplies & living, and health & beauty. Other purchases, such as music downloads, digital subscriptions and food orders, were excluded. The rationale behind this selection was to define a homogeneous comparison basis that only includes products which can be purchased online on several different platforms and for which price comparisons and e-coupons are available. In addition, only participants with complete demographic data, a minimum age of 18 years and at least one e-commerce transaction in the observation period were included. The resulting sub-sample encompasses 2819 users and 14260 transactions.

The data set includes user-level browsing and transaction-related data points from the top 200 mainstream e-commerce websites in the US and the largest alternative e-commerce, e-coupon and price comparison websites. As we are concerned with e-commerce platforms rather than with individual websites, we classified the URLs in one of the following disjoint categories: general retailers, specialized retailers, brand shops, auctions, daily deals, flash sales, price comparison and e-coupons. The classification was undertaken by two independent raters who received the same platform descriptions and selection criteria. The reports by the two raters coincided fully in their classification of the URLs.

The sample exhibits an approximate 50/50 gender split across all income groups and an age distribution of 24%-28% for ages 18-24, 25-34; 14-19% for ages 35-44, 45-54; <10% for ages 55-64, 64+. The age distribution is consistent with findings on the age distribution of the actual online shopping population in the US (Inc, 2013). Over 80% of the participants use the Internet for personal purposes for at least 5 hours a week (Table 2). Notably, the average number of transactions for each income class is fairly equal

across groups and users from the lowest income class spend a proportionally higher percentage of their income online compared to participants from higher income classes. As such a general familiarity with e-commerce can be expected for all income groups.

	Household income ('000 US\$)				
	<25	25 - 49	50-74	75 - 99	>=100
<b>Internet use</b>					
<5 hours / week	15.1%	18.4%	19.5%	20.5%	20.8%
5-16 hours / week	44.9%	40.1%	43.1%	40.5%	44.3%
>16 hours / week	40.0%	41.5%	37.4%	39.0%	34.9%
<b>Transactional data</b>					
Ø number of transactions	4.6	4.8	5.4	5.1	5.7
Ø overall spend (US\$)	163.4	167.4	201.3	202.6	230.7

**Table 2. Effects of Household Income on E-Commerce Platform Use Diversity**

### Measurement Development

#### Dependent Variables: E-commerce Use

To study the aspects of e-commerce platform diversity and the use of supporting e-commerce features, we develop a total of six dependent variables (DV). We operationalize the DVs in the following manner:

*DV1a-b: Across-website & across-platform diversity.* We adapt an entropy measure of diversification (Jacquemin & Berry, 1979) from the field of corporate diversification in order to evaluate a user's spread of transaction activity across different e-commerce platforms. The key advantage of this diversification index is that it combines the benefits of a frequency-type measure with the added insight of a classification scheme (Palepu, 1985). Due to this feature, the total diversification can be further disaggregated into (DV1a) across-website and (DV1b) across-platform diversity. It is calculated as follows:

$$DT = DR + DU = \sum_{j=1}^M P^j \left( \sum_{i \in j} P_i^j \ln \frac{1}{P_i^j} \right) + \left( \sum_{j=1}^M P^j \ln \frac{1}{P^j} \right)$$

Where: *DT* = total diversification; *DR* = across-website diversification; *DU* = across-platform diversification;  $j = 1, \dots, M$  = e-commerce platforms;  $P^j$  = share of transactions on platform  $j$ ;  $P_i^j$  = share of transactions on domain  $i$  within platform  $j$

Across-website diversity captures the spread of a user's transaction activity across websites on a given e-commerce platform, for example specialized retailers. A user who, for instance, buys a pair of shoes each at online footwear retailers footlocker.com and zappos.com will score higher than a comparable user who buys both pairs at zappos.com. Across-platform diversity in turn measures the spread of a user's transaction activity across the six e-commerce platforms defined for the purpose of this study. A user who, illustratively, purchases two pairs of Nike sneakers, one on nike.com – a brand shop – and the other on Amazon.com – a general retailer –, will again have a higher diversification score than a comparable user who purchases both pairs on Amazon.com. Furthermore, both measures take into account a user's total number of transactions within and across platforms, thereby controlling for pure volume-driven diversity.

*DV1c: Share of transactions on alternative platforms.* In order to validate the spread of transactions between mainstream (general retailer, specialized retailer, brand shop) and alternative e-commerce platforms (daily deals, flash sales, auctions), we develop a second measure of diversity by calculating the share of transactions on alternative e-commerce sites. Taking into account the data distribution, we cluster the results in 6 categories (0, 0.1%-25%, 25-49.9%, 50-74.9%, 75-99.9%, 100%) in order to enable a meaningful interpretation and differentiation between non-users, occasional users and those for whom alternative platforms are an integral part of their shopping behavior.

*DV2a-c: Use of supporting e-commerce features.* Searching for e-coupons and product prices can be seen as part of an information search taking place before a transaction (Pavlou & Fyngenson, 2006). Following previous research (Johnson et al., 2004), we define a pre-purchase period to cover the longitudinal aspect of searching and to avoid inadvertently including non-transaction-related searches

at the same time. The pre-purchase period covers 3 days prior to the transaction. This appears reasonable given the need for prices and e-coupons to be transaction-related and up-to-date. Search theory (Diamond, 1989) suggests that a search will only be executed if its marginal benefit is expected to exceed its marginal cost. Thus, use of supporting e-commerce features is only measured for transactions with a value of at least US\$ 50 to ensure a sufficiently high incentive for all income groups to search. Applying this condition results in a sub-sample of 1195 users. Three aspects related to supporting e-commerce features are measured:

(1) *DV2a*: The number of transactions for which the participant accessed price comparison sites within a period of 3 days prior to the transaction; (2) *DV2b*: The number of transactions for which the participant accessed e-coupon sites within a period of 3 days prior to the transaction; (3) *DV2c*: The number of transactions for which the participant accessed both price comparison and e-coupon sites within a period of 3 days prior to the transaction.

### **Independent Variable: Socio-economic Status**

Socio-economic status is generally defined based on household income and education (J.-Y. Jung et al., 2001; Lenhart, 2002). Since income and education have been shown to be highly correlated, income is used as a proxy for socio-economic status in this study (Chiou-Wei & Inman, 2008). Participants' household income is operationalized as an ordinal scale (1-5) in US\$25,000 increments.

### **Control Variables**

We control for the demographic variables age, gender and household size. Age and household size are operationalized as continuous variables, and gender as a binary variable (men=0, women=1). Furthermore, we take into account potential rural-urban disparities in online shopping behavior that may be driven by differences in access, availability of products and social norms (Lennon et al., 2007). This is included as a binary variable (urban=1, rural=0). In addition, we also control for Internet use intensity (measured on a three-point scale ranging from 1 = "<5 hours per week" to 3 = "16+ hours per week"), which has been shown to be a strong predictor of online buying (Goldsmith, 2002). Finally, when evaluating the use of supporting e-commerce features, we account for an individual's familiarity with e-coupon and price comparison sites by controlling for prior visits to such sites outside of the 3 days period prior to a transaction.

### **Selection of Statistical Methods**

In order to account for differences in the composition of our six dependent variables, we use ordinary least squares (OLS), ordered logit and zero-inflated regression models to test our hypotheses. The two DVs related to the entropy measure of diversification (*DV1a-b*) exhibit properties of a continuous variable as well as linearity in parameters and are therefore treated with linear multiple regression. For *DV1c*, which is operationalized as a categorical variable, we use an ordered logit model to account for the discreteness of the DV. The model predicates that a series of breakpoints exist between the DV categories (McKelvey and Zavoina 1975), as is the case for *DV1c*.

*DV2a-c* are operationalized as count variables and require special consideration. The discrete, nonlinear and nonnegative integer properties of count data imply that the parametric assumptions of OLS regression would result in biased results. A Poisson distribution is much better suited to model count data, since it is also a discrete distribution and takes on a probability value only for integer values of 0 or greater (Coxe et al., 2009). In Poisson regression models, it is important to account for variable lengths in observation periods. Unless otherwise specified, Poisson models assume equal observation periods. This is not the case in our data, where the number of times that a user accessed a price comparison and/or e-coupon website in connection with a transaction is highly dependent on the user's total number of transactions. We account for this aspect in the regression models for *DV2a-c* by applying an expansion of the Poisson model that includes an offset to control for exposure (Coxe et al., 2009). This ensures that the correct probability distribution is maintained and error structure assumptions are fulfilled.

Another common problem with count data is overdispersion, the situation in which the variance exceeds the mean (Cameron & Trivedi, 2009). In this case, it is still possible to obtain consistent coefficient estimates using a Poisson regression, but the standard errors will be deflated and the t-statistics inflated (Cox, 1983). In our dataset on the use of price comparison and e-coupon sites, we observe that the data is strongly skewed to the right with a large number of excess zeroes. Furthermore, comparably large differences between variances and means for *DV2a-c* (see Table 2) strengthen the impression of

overdispersion. A likelihood ratio test using a negative binomial regression confirmed the suspicion. For all three DV2a-c, the overdispersion parameter alpha is different from zero and significant at  $p < 0.001$ .

Given the presence of overdispersion and excess zeroes in the sample, the most appropriate model to use is the zero-inflated Poisson (ZIP) model. The ZIP model is able to handle data with excess zeroes relative to the Poisson model by supplementing a count density with a binary process (Cameron & Trivedi, 2009). Vuong's likelihood ratio test (1989) for model selection confirmed the use of a zero-inflated model over a Poisson model in all instances.

## Results

Table 3 displays summary statistics and pair-wise correlations for the variables in our study. No indications of multicollinearity could be found, which means that the independent variables are sufficiently unrelated and the standard errors not biased as a result.

Variables	Mean	S.D.	1	2	3	4	5	6
1 Age	3.69	1.51	1					
2 Gender	0.50	0.50	.08 *	1				
3 Household size	3.23	1.46	-.15 *	.06 *	1			
4 Internet use intensity	2.21	0.73	-.07 *	-.05 *	.10 *	1		
5 Urban/rural	0.72	0.45	-.09 *	-.04 *	.01	.08 *	1	
6 Household income	2.65	1.37	.11 *	-.02	.02	-.05 *	.09 *	1
7 DV1a. Across-website div.	0.09	0.22	.07 *	.08 *	-.02	.06 *	-.00	.06 *
8 DV1b. Across-platform div.	0.14	0.28	.07 *	.09 *	-.03	.03	-.02	.04 *
9 DV1c. Share alternative platforms	0.25	0.98	.01	.03	-.02	-.02	.01	.04
10 DV2a. Use of price comp.	0.32	0.88	.09 *	.03	.03	.09 *	.00	.06 *
11 DV2b. Use of e-coupons	0.23	0.86	.00	.08 *	.03	.11 *	.03	.06 *
12 DV2c. Use of both p.c. and e-c.	0.07	0.45	.01	.06 *	.05	.10 *	.01	.06
Variables			7	8	9	10	11	12
7 DV1a. Across-website div.			1					
8 DV1b. Across-platform div.			.20 *	1				
9 DV1c. Share alternative platforms			-.03	.10 *	1			
10 DV2a. Use of price comp.†			n/a	n/a	n/a	1		
11 DV2b. Use of e-coupons†			n/a	n/a	n/a	.35 *	1	
12 DV2c. Use of both p.c. and e-c.†			n/a	n/a	n/a	.54 *	.65 *	1

† Pair-wise correlations for DVa-c are based on the sub-sample  $n=1195$ ; \* $p < 0.05$

Note: Pair-wise correlations between DV1a-c. & DV2a-c. not comparable due to different sample configurations

**Table 3. Descriptive Statistics and Pairwise Correlations**

Tables 4 and 5 present the analysis results. Models 1, 3, 5, 7, 9 and 11 are the control models. Model 2 shows that income has a positive and strongly significant ( $p < 0.001$ ) effect on across-website diversity. This finding supports H1a, in which we posit that users with higher income shop on a larger variety of websites within a given platform category. Model 4 indicates moderate support for H1b, in which we predict that higher income users are also more likely to shop on a larger variety of platforms. This finding is corroborated by Model 6, which shows a positive and significant ( $p < 0.01$ ) effect of income on use of alternative e-commerce platforms, supporting H1c.

Furthermore, our findings validate hypotheses H2a-c: Model 8 indicates some support for a positive relationship between income and use of price comparison sites (H2a). Models 10 and 12 corroborate the hypotheses that users with higher income will be more likely to use e-coupons (H2b) and simultaneously use both price comparison and e-coupon sites prior to a purchase (H2c).

Variables	H1a. Across-website diversification		H1b. Across-platform diversification		H1c. Alternative platform use	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age	.009 ***	.008 **	.012 **	.010 **	.020	.007
Gender	.037 ***	.039 ***	.052 ***	.053 ***	.459 **	.473 ***
Household size	-.004	-.004	-.007	-.007	-.076	-.082
Internet use intensity	.023 ***	.024 ***	.018 *	.019 **	.036	.049
Urban/rural <sup>1</sup>	-.000	-.004	-.012	-.014	.028	-.014
Household income		.011 ***		.008 *		.133 **
F	9.40 ***	9.86 ***	9.23 ***	8.41 ***		
Adj. R <sup>2</sup>	.015	.019	.014	.016		
LR chi <sup>2</sup>					12.57 *	19.16 *

Models 1-4 are calculated using linear regressions; models 5 & 6 are calculated using ordered logit regressions; N observations = 2819; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) Urban = 1, rural = 0

**Table 4. Effects of Household Income on E-Commerce Platform Use Diversity**

Variables	H2a. Price comparison		H2b. E-coupons		H2c. Combined usage	
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Age	-.022	-.036	-.100	-.119	-.005	-.463 *
Gender	.013	-.008	.070	.010	-.210	-.753 *
Household size	.091	.080	.011	.017	.154	.206
Internet use intensity	-.036	-.033	.268	.246	-.131	-.192
Urban/rural <sup>1</sup>	.054	.063	-.197	-.286	.656	-.268
Prior site visits	18.0	17.9	17.2	17.4	18.2	17.5
Household income		.084 *		.130 **		.271 **
Total transactions	-----exposure term-----					
LR chi <sup>2</sup>	207.4 ***	211.8 ***	219.4 ***	226.7 ***	82.83 ***	88.96 ***
AIC	1304.1	1301.7	911.7	906.4	362.2	358.1
BIC	1370.2	1372.9	977.8	977.6	428.4	429.3

All models are calculated using zero-inflated poisson regressions ; N observations = 1195; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) Urban = 1, rural = 0

**Table 5. Effects of Household Income on Use of Supporting E-Commerce Features**

## Discussion

This study set out to explore how individuals differ in their use of e-commerce as a function of their socio-economic status and, in turn, whether e-commerce amplifies or attenuates digital inequality. Our findings particularly contribute to research on digital inequality and the societal impact of ICT. First and foremost, the results underscore that digital inequality is a prevalent societal issue, which not only has a first-order effect related to unequal ICT access but also a second-order effect resulting from inequality related to differential ICT use. Despite undisputed advances in providing ICT access (OECD, 2013), ICT in general, and the Internet in particular, have so far failed to deliver on the promise of serving as equal opportunities platforms (Hargittai, 2010). In fact, as an unintended social consequence, the Internet might even perpetuate socio-economic stratification. Some scholars maintained that this divide will disappear with increasing Internet access over time (Compaine, 2001). Our results, however, tell a different story: even at levels of comparable Internet access, individuals who are already socio-economically advantaged are able to draw greater benefits from e-commerce use than do their disadvantaged peers. With the increasing pervasiveness of e-commerce applications in our everyday lives and a growing relevance of Internet based self-service solutions, these differences in e-commerce use could further widen the economic welfare gap between the rich and the poor. In addition, the societal impacts of differential e-commerce use patterns might be indicative for a variety of Internet use types such as e-learning or online job search where differential use among socio-economic classes might translate into unequal education and job opportunities.

Moreover, this study is, to the best of our knowledge, the first to empirically test and validate the long hypothesized relationship of an e-commerce divide. Digital inequality specifically in the context of e-commerce has so far garnered limited attention, but is of key importance given its immediate economic implications. Prior research (Riggins & Dewan, 2005) has only theorized how socio-economic status negatively impacts the use of sophisticated e-commerce functionalities. Therefore, our findings represent an important step towards a more comprehensive understanding of digital inequality in the context of e-commerce.

In addition, our novel concept of use diversity could be particularly relevant to digital inequality research across different ICTs because it captures individual use patterns in multi-channel, multi-application environments. The less diverse use patterns of socio-economically disadvantaged users found in the context of e-commerce may be indicative for a variety of technological contexts, in particular those that offer a large range of use possibilities. Smartphone applications, for instance, are a case of a highly fragmented marketplace in which diverse use is likely to result in a higher payoff. Each application in itself generally only offers a limited set of functionalities; hence the ability to navigate across the marketplace and to identify, evaluate, and use a range of applications is critical to drawing a benefit.

This study also has several important theoretical implications for information systems research at large. Most importantly, we develop a more holistic conceptualization of e-commerce system use for the study of technology acceptance. Drawing on Benbasat and Barki (2007), we propose that the operationalization of e-commerce use needs to go beyond the traditional notion of a single purchase and has to account for the multi-dimensional context in which transactions take place. The advantages of such an extended behavioral operationalization of use lies in a “more faithful representation of usage activities that users engage in, [and] stronger links with salient outcome variables” (Benbasat and Barki 2007: p.215). Our conceptualization of e-commerce use contributes to the understanding of online shopping in a more holistic and nuanced manner, in particular with regard to economic utility-enhancing activities.

Finally, a major methodological contribution of our study is the introduction of clickstream data as an empirical basis for technology adoption research. As Straub and Burton-Jones (2007) have noted, one of the most critical methodological issues underlying TAM is the high risk of common method variance as a result of common-rater effects and self-report bias. Typically, respondents have to indicate both their attitude towards a particular ICT, e.g. how useful they find it, and whether they use or intend to use it. Consequently, the bivariate correlations between DV and IVs risk being severely skewed. The use of clickstream data allows overcoming these methodological limitations. In addition, clickstream data tracks actual rather than intended behavior over a sustained period of time avoiding problems with time-variant intentions and potential unreliability of self-reported behavioral attitudes (Podsakoff et al., 2003). While clickstream data is not without its limitations either (Bucklin & Sismeiro, 2009), technology acceptance researchers stand to benefit from integrating clickstream data tracking actual use with self-report surveys measuring behavioral antecedents.

Above and beyond contributions to theory, our study has implications for policy makers and for business practitioners alike. Understanding how socioeconomically advantaged and disadvantaged users differ in their use of e-commerce enables policy makers to potentially devise countermeasures and businesses to develop strategies to adequately cater to different societal groups.

On a public policy level, our study highlights that digital inequality is a substantial societal issue, even in developed countries such as the US. Despite a fast increase of Internet access, Internet use behavior still differs between socio-economic groups and reinforces societal stratification. Given that the Internet can be a catalyst for economic development and – when used effectively – possesses the potential to equalize social disparities (Anderson et al., 1995), unleashing this potential should be a priority for public policy. More specifically, our findings underline the importance of developing not only access-based initiatives but also use-oriented measures. Existing governmental initiatives targeting Internet use, such as the US National Broadband Plan, have largely focused on providing access. However, our study suggests that this is not sufficient to ensure the same online opportunities to all groups in society. The traditional assumption of homogeneous ability to use ICT needs to be replaced by a more nuanced understanding, leading to more tailored policies which take socio-economic status into account. Policy interventions focusing on Internet education and digital skills could help bridge the current gap and could be added to the educational agenda in the context of broader ICT education at secondary schools, in particular in underprivileged districts. Furthermore, consumer protection agencies could be



empowered to raise awareness and promote knowledge dissemination about Internet use in general and e-commerce in particular.

Online businesses and providers of e-coupon and price comparison sites could use the insights on differential e-commerce use between socio-economic groups in order to make their services more attractive to the socio-economically disadvantaged which currently might not be key customers. By effectively targeting currently alienated socio-economic groups, businesses have the potential to expand their customer base and generate additional revenue. For instance, our theorizing highlights that key hurdles – particularly for the socio-economically disadvantaged – associated with shopping on a large range of platforms are the complexity and the perceived risk of creating a unique personal account for each website. In some cases, particularly flash sale sites, users are required to sign-up before even being able to view the products on offer. An increased adoption of integrated single sign-on systems such as “Login with Amazon”, “Login with Facebook” or Google+ by online retailers could remove such frictions.

## **Limitations and Further Research**

We acknowledge some theoretical and empirical limitations to our study, which call for further research. Further, we highlight additional promising avenues for research originating from our findings.

A common critique in technology acceptance research has been the focus on explaining a single behavior conceptualized in a narrow manner (Benbasat & Barki, 2007) at one point in time. Such a one-dimensional view is not reflective of the multifaceted uses of technology and the dynamism inherent in technological change. In today’s fast-paced digitalized world, the realm of online functionalities is constantly evolving. While our proposed conceptualization of e-commerce use aims to capture online shopping more fully in its complexity and variety than current constructs, it makes no claim to being exhaustive. Thus, we urge subsequent research to refine and extend our concept of e-commerce use. In particular, e-commerce applications relating to services such as e-banking, insurance and peer-to-peer marketplaces (e.g. for accommodation/travel) are gaining increasing importance and offer an interesting avenue for further research. In addition, applying a more in depth conceptualization of system use to other information systems can provide a particular rich basis for understanding individual use patterns and their implications.

Further, the notion of use diversity developed in this study can provide an insightful lens for information systems scholars seeking to capture ICT use in multi-technology, multi-application environments such as information search and browsing patterns, areas in which complexity of online behavior is the relevant research variable. To this end, the entropy measure of diversification proposed in this study may serve future researchers as a useful measure of use diversity. The concept of use diversity may also be of interest to digital inequality researchers, especially with regard to the broader issue of complexity management. Recent digital inequality research has sought to explain differential ability of socio-economic groups to use the Internet by studying skill-related aspects such as online navigation skills (van Deursen & van Dijk, 2010). However, more fundamental, cognitive-psychological drivers such as the ability to multitask or handle information overload may in fact lie at heart of why the socio-economically disadvantaged less often fully leverage the breadth of Internet opportunities. Future research may benefit from exploring the connection between diversity in use patterns and digital inequality in more detail, from both psychological and skills perspectives.

The clickstream data used in our study has advantages in avoiding typical weaknesses of cross-sectional data such as self-report bias and common rater effects (Podsakoff et al., 2003), yet has limitations with regard to uncovering the motivations behind observed behavior. Existing research on the impact of socio-economic status on the behavioral TAM dimensions allows us to theorize why the socio-economically disadvantaged are less likely to use certain functionalities. Empirical investigations into the behavioral antecedents of digital inequality within the specific context of e-commerce would contribute to further substantiating this theoretical basis. We therefore encourage the replication of our findings using clickstream data in conjunction with surveys or structured interviews in order to enrich the understanding of the factors driving differential behavior between advantaged and disadvantaged groups.

Finally, this research only captures online shopping behavior on home PCs and in a voluntary setting. As online shopping increasingly migrates from the traditional PC to mobile devices such as tablets and smartphones, future research should investigate the generalizability of our findings across channels. Furthermore, given that the observed use patterns occurred in a voluntary setting, scholars should investigate whether differential use persists if online use is mandatory as it might be the case for some

e-government dealings. Moreover, technology acceptance patterns have been found to be influenced, for example by culture (Im et al., 2011). It would be prudent to examine if our findings from the US can be replicated in other countries.

## **Conclusion**

This study presents a new perspective on how ICT in general and e-commerce in particular relate to the societal phenomenon of digital inequality. Following researchers' call to better understand digital inequality in the context of e-commerce, we introduce a nuanced conceptualization of e-commerce use and investigate how individuals from different socio-economic backgrounds differ in their online shopping behavior. We empirically examine this behavior using clickstream data. Our findings reveal that despite equal access, significant differences in e-commerce use behavior between the socio-economically advantaged and disadvantaged exist. Even though Internet applications such as e-commerce could serve as a catalyst to reduce existing socio-economic disparities, this potential is so far not being realized. In this respect, our research constitutes an important step towards a better understanding of how ICT can impact our society for better or worse and which measures could be devised to influence this impact.

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**[Supplement B]**

**Second-order digital inequality: The case of  
e-commerce (presentation held at ICIS 2014)**



# Second-Order Digital Inequality: The Case of E-Commerce

International Conference on Information Systems

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Prof. Dr. Andreas König, Dr. Lorenz Graf-Vlachy, Dr. Jan Mammen



## Agenda

- 1. Research Motivation and Hypotheses**
2. Methodology
3. Results
4. Discussion and Further Research

1. RESEARCH MOTIVATION AND HYPOTHESES

## Ever since its inception, scholars have discussed the impact of the Internet on society

### Hopes and apprehensions at the Internet's inception



- Internet might provide people with **access to creating value and thus fosters societal wealth and well-being** (Hargittai 1999, Madden 2000)
- Internet-based technologies could level playing field between societal strata and **reduce social inequality** (Anderson 1995)
- Internet could lead to „**increasing inequalities**, improving the prospects of those [...] in privileged positions while denying opportunities for advancement for the underprivileged“ (Hargittai 2003)
- Phenomenon described by term „**digital inequality**“ referring to differences between individuals regarding their access and ability to use Internet-based ICT (Di Maggio et al. 2001)

1. RESEARCH MOTIVATION AND HYPOTHESES

## Current research aims to focus on „second order effects“ of digital inequality: users’ ability to use the Internet

### First-order digital inequality<sup>1</sup>

- **Focus on ICT access** as fundamental inequality driver (e.g. DiMaggio et al. 2001; Katz and Rice 2002)
- Focus of scholarly debate since early 90s and **mainly explored in descriptive manner**
- Of continued importance with regard to **base-of-the-pyramid ICT users**, mainly in developing markets

### Second-order digital inequality

- Given widespread Internet availability & access, research focus has shifted to the **ability to use the Internet (2nd order effect)** (DiMaggio and Hargittai 2001)
- The key hypothesis is that the **manner of ICT use further perpetuates existing inequalities**
- Focus on **exploring existence/ implications of digital inequality in central and potentially beneficial Internet applications** such as info search (van Deurtsen 2012) e-government participation (Belanger and Carter 2009) and capital-enhancing website use (Zillien and Hargittai 2009)
- The aim is to explore how people use the Internet for **opportunity creation** in order to **bridge growing divides** (e.g. information, skill, economic opportunity divide)

<sup>1</sup> The terms "first-order digital inequality" and "digital divide" are used interchangeably

1. RESEARCH MOTIVATION AND HYPOTHESES

## Recently, e-commerce has emerged as an additional area of opportunity creation within the digital inequality discussion

### Growing significance of e-commerce

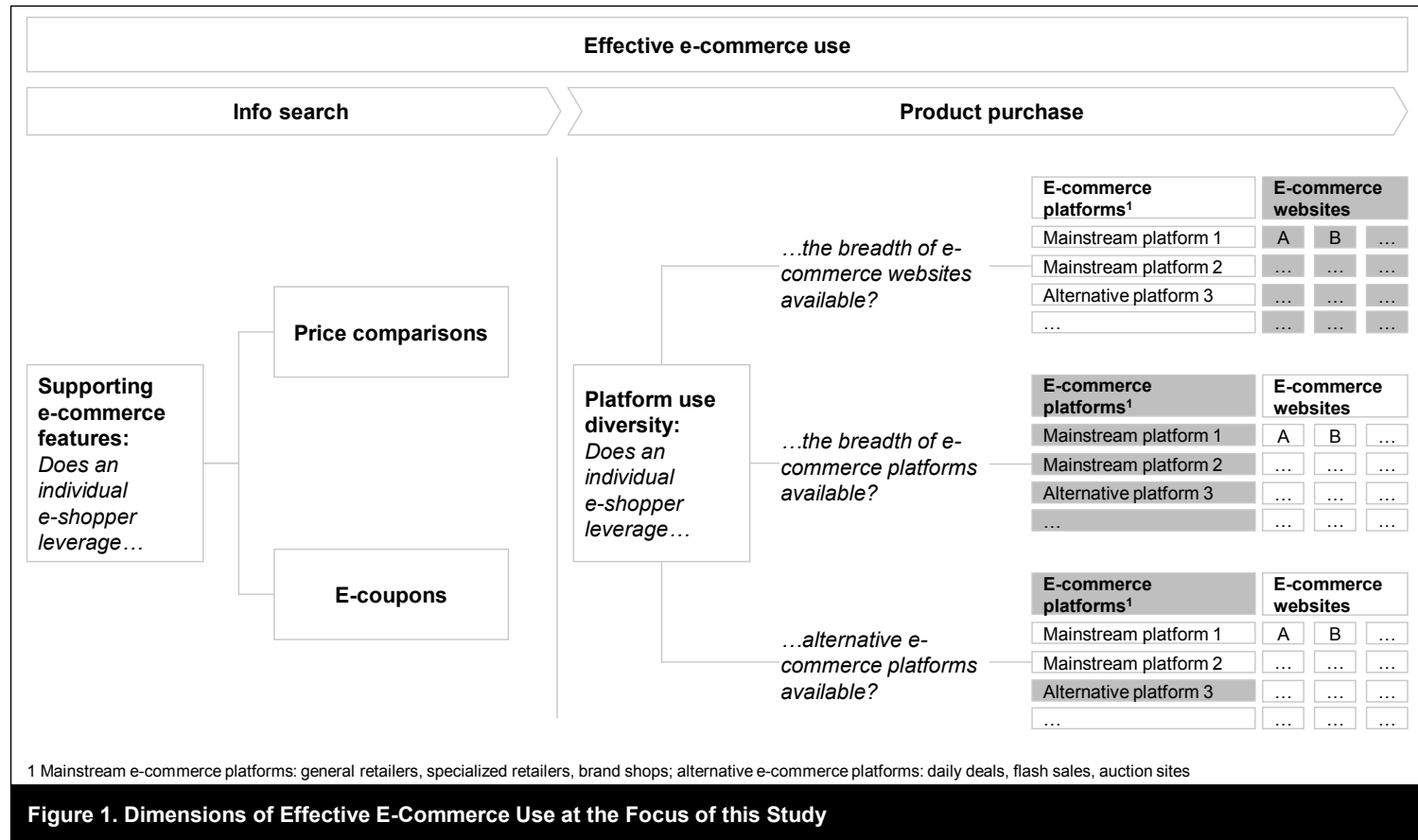
- E-commerce captures **substantial share of global business** exceeding US\$1 trillion (eMarketer 2013)
  - U.S. citizens alone spent US\$263 billion online (U.S. Department of Commerce 2014) and are expected to spend **US\$370 billion** by 2017 (Forrester Research 2013)
  - Wide range of e-commerce platforms and formats have evolved that help individuals to **optimize the economic outcome of purchases**, e.g. price comparisons, auctions, e-coupons
- ➔ Users who are able to **shop more effectively** by leveraging e-commerce functionalities can potentially generate as substantial **economic surplus**

### Digital inequality in the context of e-commerce

- Little scholarly attention has so far been devoted to **digital inequality in the context of e-commerce**
  - Limited **empirical evidence** available suggests an **e-commerce divide** exists (Riggins and Dewan 2005)
  - Prior research (Akther 2003; Howard et al. 2001; Zillien and Hargittai 2009) suggests that contrary to homo-economicus expectations, those with the **least resources** might be **less likely to fully leverage e-commerce functionalities**
- ➔ Call from scholars for research that **better conceptualizes** and studies digital inequality **in the context of e-commerce** (Riggins and Dewan 2005)

1. RESEARCH MOTIVATION AND HYPOTHESES

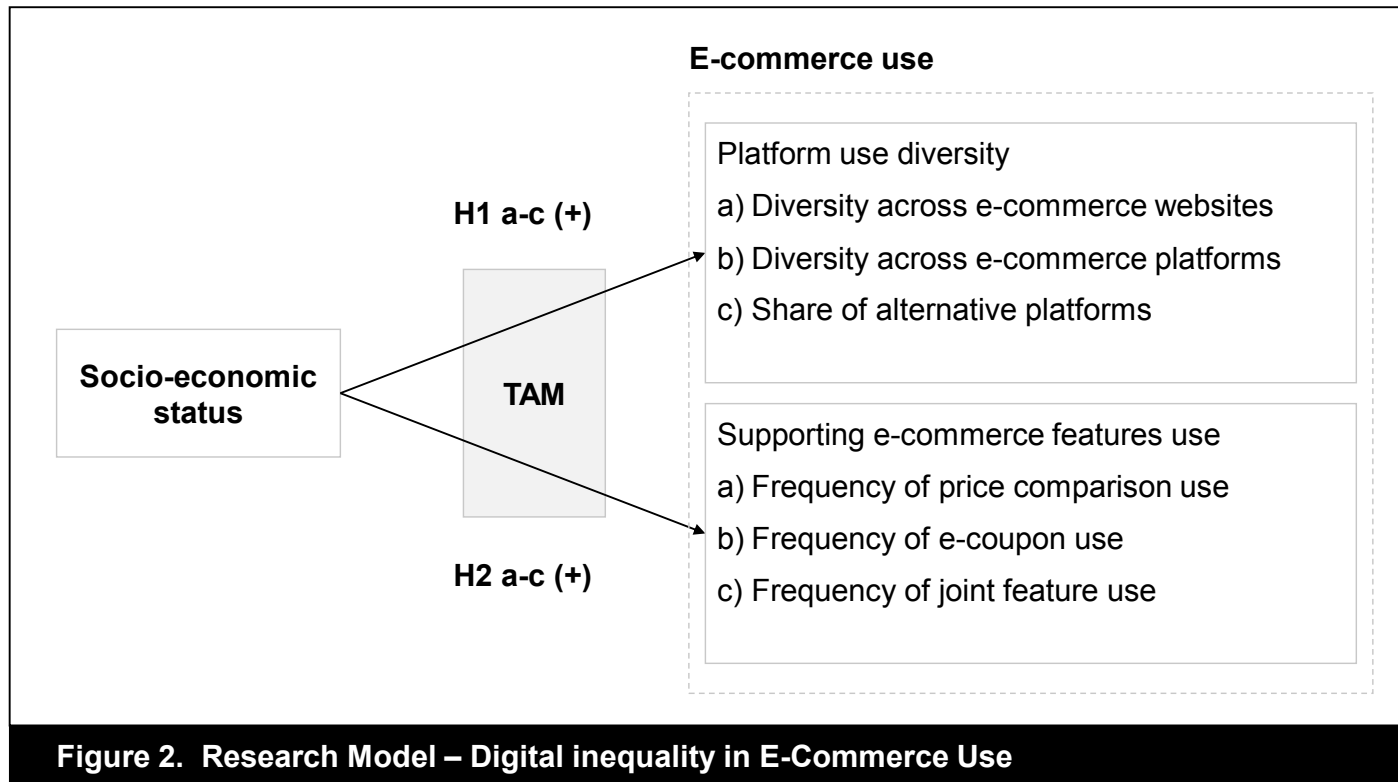
**To study e-commerce use a concept of effective use is required that takes into account multiple steps of the purchasing process**



1. RESEARCH MOTIVATION AND HYPOTHESES

**We aim to investigate if e-commerce amplifies or attenuates digital inequality by measuring the impact of SE-status on e-commerce use**

**RQ: How do individuals vary in their e-commerce use as a function of their socio-economic status and, as a result, does e-commerce amplify or attenuate digital inequality?**



**Figure 2. Research Model – Digital inequality in E-Commerce Use**

1. RESEARCH MOTIVATION AND HYPOTHESES

**We draw on TAM (Davis 1989) to build hypotheses on the relation between an individual's socio-economic status and e-commerce use**

**Table 1. Using TAM constructs to link socio-economic status and e-commerce use**

TAM construct	Definition	Relative importance of construct depending on socio-economic status	Support for identified relative importance from existing literature	Illustration of specific TAM construct influence on e-commerce use (examples)	
				Platform use diversity	Supporting e-commerce features
<b>Perceived ease of use (PEOU)</b>	Subjective degree of effort required to shop online (Davis 1989)	Relatively <b>higher</b> for the <b>socio-economic advantaged</b>	Van Deursen (2012), Fan and Eaton (2001), Hoffman (2003), Rice and Katz (2003)	(+) Requires PEOU to manage e.g. multiple interface complexity	(+) Requires PEOU, e.g. evaluate price comparison search results
<b>Utilitarian motivation</b>	Individual perception of gains that can be derived from shopping online (Davis 1989)	Relatively <b>higher</b> for the <b>socio-economic advantaged</b>	Bonfadelli (2002), van Deursen and van Dijk (2010), Hargittai and Hinnant (2008), Nomis (2001)	(+) Provides utilitarian benefit of cost savings, e.g. through using auctions or daily deals	(+) Provides utilitarian benefit of cost savings, e.g. thorough price transparency
<b>Hedonic motivation</b>	Degree to which an individual can derive enjoyment from online shopping (Childers et al. 2001)	Relatively <b>higher</b> for the <b>socio-economic disadvantaged</b>	Aneshensel (1992), Hsieh et al. (2008), Mathwick et al. (2001), Parker and Endler (1996)	(+) Provides hedonic benefits like e.g. novelty, thrill and feeling of escaping reality	(+) Hedonic benefits limited, e.g. to the joy of searching
<b>Perceived Risk</b>	Individual assessment of the risks associated with online shopping related to information misuse, product benefits and functionality inefficiency (Glover and Benbasat 2010)	Relatively <b>higher</b> for <b>socio-economic disadvantaged</b>	Schechter (2007), McLeod and Kessler (1990), Bhatnagar and Ghose (2004), Shaw (1996)	(-) Increases risk, e.g. through multiple disclosure of personal and financial data	Not applicable



## Agenda

1. Research Motivation and Hypotheses
- 2. Methodology**
3. Results
4. Discussion and Further Research

2. METHODOLOGY

**We tested our hypotheses on a unique set of clickstream data, which represents a record of an individual’s actual online activities**

**Clickstream database**



- Total panel: ~20,000 users in the US
- Tracking period: May – October 2012
- Data captured:
  - Full site URL, site name, time stamp
  - Precursor / successor website
  - Full purchase and basket details (\$ spent, item-level description)
  - Search strings (user input)
  - Demographics (e.g. age, gender, income range, zip, ...)
- Limitation to 4 product categories: apparel & accessories, consumer electronics, home supplies & living, and health & beauty
- Categorization of top 200 e-commerce websites in US in 6 disjoint categories
- Min. requirements: 18+ years, min. 1 transaction, complete demographics
- 2,819 users
- 14,260 e-commerce transactions

**Sample characteristics**

**Table 2. Demographic Characteristics of Sample (n = 2,819)**

	Household income (US\$)				
	<25000	25000 - 49999	50000 - 74999	75000 - 99999	>=100000
<b>Age</b>					
18 - 24	32.1%	29.7%	26.1%	24.7%	25.4%
25 - 34	28.3%	23.7%	23.5%	21.4%	19.6%
35 - 44	16.3%	19.0%	18.8%	23.6%	18.2%
45 - 54	12.9%	14.3%	12.0%	14.0%	19.9%
55 - 64	7.3%	9.1%	11.0%	8.7%	10.7%
65+	3.1%	4.2%	8.6%	7.6%	6.3%
<b>Gender</b>					
Female	50.1%	50.7%	50.9%	51.1%	44.8%
Male	49.9%	49.3%	49.1%	48.9%	55.2%
<b>Household size</b>					
1 person	14.4%	11.9%	9.3%	11.5%	10.1%
2 people	23.2%	28.5%	28.5%	25.8%	22.8%
3 people	22.8%	17.6%	17.3%	21.4%	23.7%
4 people	15.1%	17.5%	20.9%	21.9%	19.4%
5 people	17.2%	17.8%	16.7%	12.9%	20.1%
6+ people	7.3%	6.7%	7.3%	6.5%	3.9%
<b>Internet use</b>					
<5 hours / week	15.1%	18.4%	19.5%	20.5%	20.8%
5-16 hours / week	44.9%	40.1%	43.1%	40.5%	44.3%
>16 hours / week	40.0%	41.5%	37.4%	39.0%	34.9%
<b>Transactional data</b>					
Ø number of transactions	4.6	4.8	5.4	5.1	5.7
Ø overall spend (US\$)	163.4	167.4	201.3	202.6	230.7

2. METHODOLOGY

**A range of measures were developed to capture the model variables and statistical methods selected accordingly for the analysis**

	Variables	Measure	Statistical method
DVs	Platform use diversity <ul style="list-style-type: none"> <li>▪ Diversity across e-commerce websites</li> <li>▪ Diversity across e-commerce platforms</li> <li>▪ Share of alternative platforms</li> </ul>	Entropy measure of diversification (Jacquemin and Berry 1979) $DT = DR + DU = \sum_{j=1}^M P^j \left( \sum_{i \in j} P_i^j \ln \frac{1}{P_i^j} \right) + \left( \sum_{j=1}^M P^j \ln \frac{1}{P^j} \right)$ Share of total transactions, clustered into ordinal scale (1-6)	OLS  Ordered logit
	Supporting e-commerce features use <ul style="list-style-type: none"> <li>▪ Frequency of price comparison use</li> <li>▪ Frequency of e-coupon use</li> <li>▪ Frequency of joint feature use</li> </ul>	Count variable <ul style="list-style-type: none"> <li>▪ # transactions in which feature was used</li> <li>▪ # transactions in which feature was used</li> <li>▪ # transactions in which feature was used</li> </ul>	Zero-inflated Poisson with offset for exposure (Coxe et al. 2009)
IV	Household income as proxy for socio-economic status (Jung et al. 2001; Chiou-Wei and Inman 2008)	Ordinal scale (1-5) in US\$25,000 increments	
CVs	<ul style="list-style-type: none"> <li>▪ Age</li> <li>▪ Gender</li> <li>▪ Household size</li> <li>▪ Rural/urban</li> <li>▪ Internet use intensity</li> <li>▪ Prior visits to price comparison / e-coupon sites</li> </ul>	<ul style="list-style-type: none"> <li>▪ Continuous variable</li> <li>▪ Binary variable</li> <li>▪ Continuous variable</li> <li>▪ Binary variable</li> <li>▪ Ordinal scale (1-3)</li> <li>▪ Binary variable</li> </ul>	

## Agenda

1. Research Motivation and Hypotheses
2. Methodology
- 3. Results**
4. Discussion and Further Research

3. RESULTS (I/II)

**We find positive and significant support for our hypotheses on the effect of household income on e-commerce platform use diversity**

Hypotheses:	Supporting evidence:
<ul style="list-style-type: none"> <li>✓ H1a: higher income users more likely to shop on a larger variety of websites within a platform category</li> <li>✓ H1b: higher income users more likely to shop on a larger variety of platforms</li> <li>✓ H1c: higher income users more likely to use alternative platforms</li> </ul>	<ul style="list-style-type: none"> <li>▪ Income has a positive and strongly significant (p&lt;0.001) effect on across-website diversity</li> <li>▪ Moderate support that income has a positive effect on across-platform diversity</li> <li>▪ Positive and significant indication of income effect on share of alternative platform use</li> </ul>

**Table 3. Effects of Household Income on E-commerce Platform Use Diversity**

Variables	H1a. Across-website diversification		H1b. Across-platform diversification		H1c. Alternative platform use	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age	.009 ***	.008 **	.012 **	.010 **	.020	.007
Gender	.037 ***	.039 ***	.052 ***	.053 ***	.459 **	.473 ***
Household size	-.004	-.004	-.007	-.007	-.076	-.082
Internet use intensity	.023 ***	.024 ***	.018 *	.019 **	.036	.049
Urban/rural <sup>1</sup>	-.000	-.004	-.012	-.014	.028	-.014
Household income		.011 ***		.008 *		.133 **
F	9.40 ***	9.86 ***	9.23 ***	8.41 ***		
Adj. R <sup>2</sup>	.015	.019	.014	.016		
LR chi <sup>2</sup>					12.57 *	19.16 *

Models 1-4 are calculated using linear regressions; models 5 & 6 are calculated using ordered logit regressions; N observations = 2819; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) Urban = 1, rural = 0

3. RESULTS (II/II)

**Similarly, we find positive and significant support for the effect of household income on the use of supporting e-commerce features**

Hypotheses:	Supporting evidence:
<ul style="list-style-type: none"> <li>✓ H2a: higher income users likely to use price comparisons more frequently when shopping online</li> <li>✓ H2b: higher income users likely to use e-coupons more frequently when shopping online</li> <li>✓ H2c: higher income users likely to use both features jointly more frequently when shopping online</li> </ul>	<ul style="list-style-type: none"> <li>▪ Moderate support for positive relationship between income and use of price comparison sites</li> <li>▪ Income has a positive and significant effect on e-coupon use</li> <li>▪ Positive, significant indication of income effect on combined use of price comparisons &amp; e-coupons</li> </ul>

**Table 4. Effects of Household Income on Use of Supporting E-commerce Features**

Variables	H2a. Price comparison		H2b. E-coupons		H2c. Combined usage	
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Age	-.022	-.036	-.100	-.119	-.005	-.463 *
Gender	.013	-.008	.070	.010	-.210	-.753 *
Household size	.091	.080	.011	.017	.154	.206
Internet use intensity	-.036	-.033	.268	.246	-.131	-.192
Urban/rural <sup>1</sup>	.054	.063	-.197	-.286	.656	-.268
Prior site visits	18.0	17.9	17.2	17.4	18.2	17.5
Household income		.084 *		.130 **		.271 **
Total transactions	-----exposure term-----					
LR chi <sup>2</sup>	207.4 ***	211.8 ***	219.4 ***	226.7 ***	82.83 ***	88.96 ***
AIC	1304.1	1301.7	911.7	906.4	362.2	358.1
BIC	1370.2	1372.9	977.8	977.6	428.4	429.3

All models are calculated using zero-inflated poisson regressions ; N observations = 1195; p\* < .05, \*\*p < 0.01, p\*\*\* < 0.001; 1) Urban = 1, rural = 0

## Agenda

1. Research Motivation and Hypotheses
2. Methodology
3. Results
- 4. Discussion and Further Research**

4. DISCUSSION AND FURTHER RESEARCH

## Our findings have implications both for theory and managerial practice

### Contributions to theory

- Digital inequality is a **substantial societal issue**, even in developed countries such as the US
- **First study to empirically test and validate** the existence of a second-order divide **within e-commerce** in this scale
- Introduction of ICT **use diversity** concept to digital inequality research
- Introduction of **clickstream data** as an empirical basis for technology adoption research
- **Conceptualization of e-commerce use** beyond the traditional notion of a single purchase accounting for a multi-dimensional context

### Implications for practice

- Findings underline the importance of developing **not only access-based initiatives** but also **use-oriented policy interventions**
  - Traditional assumption of homogeneous abilities to use ICT need to be replaced by a more **nuanced understanding of target group differences**
  - Policy interventions could, e.g., take the form of **educational modules** in schools on effective Internet use, e.g., teaching “smart” ways to shop online
- Online businesses should use insights on differential e-commerce use between socio-economic groups to **make services more attractive to the disadvantaged** which currently might not be customers



#### 4. DISCUSSION AND FURTHER RESEARCH

### Potential avenues for future research

- **Refinement and extension of conceptualization of general system use** (as proposed by Barki and Benbasat 2007) and in particular **e-commerce use**, e.g. extension to e-services such as e-banking, peer-to-peer market places for accommodation and travel
- **Application of notion of diversity in broader IS field** to capture ICT use patterns in a multi-technology and multi-application environment
- Exploration of the **connection between diversity in use patterns and digital inequality** from both a **psychological and skill perspective**
- Further investigation into **behavioral antecedents of digital inequality** within specific context of e-commerce, e.g. replication of our findings using clickstream data in conjunction with surveys or structured interviews
- **Testing of further moderators** that influence effect of socio-economic status should be explored, e.g. impact of children on parents' behavior (Correa et al. 2013) or effect of personal network exposure (Hsieh et al. 2008)
- Accounting for omni-channel nature of e-commerce by including further devices in research setup
- Verifying generalizability of findings, e.g. testing influence of cultural idiosyncrasies (e.g. German thriftiness)