Social influence in technology adoption:

Taking stock and moving forward

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This article was published in *Management Review Quarterly*.

The final publication is available at http://link.springer.com

https://doi.org/10.1007/s11301-017-0133-3

Acknowledgements

We would like to thank Hendrike Werwigk for editorial support. We further acknowledge helpful comments from participants of the 25th European Conference on Information Systems.

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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 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. Consequently, this paper sets out to review how social influence has been conceptualized in technology adoption research. In so doing, this paper attempts to inform researchers' understanding of the construct, reconcile its myriad conceptualizations, constructively challenge extant approaches, and provide impulses 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 survey-based and US/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-theoretical 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

1. Introduction

The impact of social influence on human behavior in general and information technology adoption in particular has been widely acknowledged (Triandis 1980; Venkatesh et al. 2003; Asch 1953). 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 (Kelman 1958; French & Raven 1959). In 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 et al. 1990). As information and communication (ICT) technologies increasingly pervade all aspects of our lives, understanding what influences individuals' decisions 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 technologies succeed (Tsai & Bagozzi 2014; Junglas et al. 2013). 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 the perceived usefulness of a technology (Williams et al. 2014; Wang & Chou 2014) and people's behavioral intention to adopt the technology (Chatterjee et al. 2015; Sun et al. 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 perform a behavior (Fishbein & Ajzen 1975). Others, like social identity, consider social influence as a function of an individual's emotional and evaluative identification with a group (Tajfel 1978). These starkly different interprations of social influence pose a challenge for technology adoption research.

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 calls into question the validity of its present conceptualization. Many studies have found support for social influence on IT adoption (Dickinger et al. 2008; Sykes et al. 2009; Chatterjee et al. 2015), while many others have not (Pavlou & Fygenson 2006; Chan et al. 2010; Zhang et al. 2006). Some studies found an effect for women, but not men (Venkatesh & Morris 2000); for novice, but not experienced users (Karahanna et al. 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 (Malhotra & Galletta 2005; Gallivan et al. 2005; Bagozzi 2007). 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 et al. 2005; Wang et al. 2013).

As a result, prominent IS scholars have expressed the need to better understand social influence itself and the relationship between social influence and technology adoption (Karahanna & Limayem 2000; Mathieson 1991; Legris et al. 2003). Notably, Bagozzi (2007) advocated that variables that account for group, social, and cultural behaviors and that go beyond normative influence should be added to 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 et al. 2013). While this increasing pluralism promises to more fully capture the range of social impulses governing technology adoption, it also contributes to an increasingly fragmented landscape of constructs that challenges the conceptual integrity of the field.

Therefore, we set out to conduct a systematic review of social influence in technology adoption research 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 cotribution, 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 guide 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, the 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. Finally, social influence research on technology adoption often does not differentiate among social referents and is heavily reliant on survey-based and US/China-centric samples, which jeopardizes the generalizability and predictive validity of its findings. Building on these observations, we 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 meta-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 et al. 2010; Venkatesh et al. 2003), or adjacent literature domains, such as organizational and psychology research (Borgatti & Foster 2003; Cialdini & Goldstein 2004; Adler & Kwon 2002). In addition, our 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.

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 (Triandis 1980; Asch 1953; Fulk et al. 1990), 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; French & Raven 1959; Cialdini & Trost 1998), organizational behavior (Pillutla & Chen 1999), marketing (Algesheimer et al. 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 et al. 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 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.

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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 (Deutsch & Gerard 1955; Karahanna et al. 1999; Burnkrant & Cousineau 1975). For example, if a superior suggests that the focal individual is expected to use a particular technology, the latter may do so to conform with the expectations but without altering his or her belief structure—a case of normative influence. In contrast, 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. 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 (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 individiual's network and take into account the characteristics of that network. Network 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 et al. 2008) and electronic health software (Venkatesh et al. 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 (Lou et al. 2000; Cho 2011). 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.

3. Research methodology

In order to explore how social influence has been studied in technology adoption research, we 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 taken to avoid an unmanageable sample of articles with limited value. In addition, only academic, peer-reviewed journal articles in English from 2000 through 2015 were considered. These restrictions naturally constitute a trade-off between comprehensiveness on the one hand and relevance on the 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), we started by reviewing papers published in the IS Senior Scholars' Basket of Journals for relevant studies. The Senior Scholars' Basket of Journals encompasses eight IS journals with 2016 Scimago Journal Rank impact factors between 0.91 and 6.69 (and an average of 2.94), namely 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*. This selection represents the official canon of the *Association for Information Systems* of the field's top journals, is "intended to provide more consistency and meaningfulness to tenure and promotion cases," and has been adopted at schools around the world (AIS 2011). In addition, given the interdisciplinary nature of the IS field, we conducted a comprehensive database search of ABI/INFORM and Business Source Premier, two of the most comprehensive databases of peer-reviewed literature in relevant disciplines, using the keywords "technology acceptance," "technology use," and "technology adoption" (as identified through an exploratory reading of the literature and validated with fellow IS researchers) in combination with "social," (thus also capturing terms like "social influence," "social norm," "subjective norm," "social capital," etc.). Together, this resulted in a preliminary sample totaling 642 papers (Figure 2). Following an initial screening of titles and abstracts, 418 papers were excluded. The large number of exclusions was driven, e.g., by studies whose dependent variable was not technology adoption or use (e.g., Sarker et al. 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). Following 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 to ensure academic relevance and research quality.[1] This reduced the sample from 224 to 131 papers. Based on a full reading of these papers, 44 more papers were excluded because they did not fulfill our requirements (e.g., social influence was not an independent variable or technology adoption was not a dependent variable), and an additional 26 papers were added through forward and backward integration, i.e., they were identified as relevant sources because other papers in our sample referred to them (Webster & Watson 2002). In total, 113 journal articles were selected for in-depth coding.

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Third and finally, the 113 selected papers were coded systematically to gather insights on their conceptual and methodological approaches to studying social influence. The articles were coded by one of the authors. To assess interrater agreement, another author coded a random subset of 15 articles, yielding no differences in coding. 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, or 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

[1] 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. Using the year 2011 as a cut-off allowed for a roughly stable number of papers per year in the final sample.

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, and directional impact of social influence. Table A1 in the online appendix provides detailed data as per the key coding categories.

4. Taking stock: Findings and implications

The literature review suggests that there exists some variation in research on social influence research on technology adoption, but that many studies conform to a dominant design. The prototypical study on social influence in technology adoption in our sample of 113 papers is empirical (110 papers), purely quantitative (103 papers), and has the following four features: First, although there is a wide range of social influence conceptualizations and many studies use a mixed social influence construct, i.e., one that incorporated several constructs (70 papers), there is a substantial skew towards the concept of subjective norm/social norm (80 papers), and more generally towards compliance-based definitions (93 papers). Second, our analysis reveals that social influence is overwhelmingly examined at the individual level of analysis (99 papers). Third, social influence has been primarily studied with respect to non-social technologies (which were addressed by only 31 papers). Finally, social influence research on technology adoption often does not differentiate among social referents and is heavily reliant on survey-based (102 papers) and US/China-centric samples. We explore each of these features in greater 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, we 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. We outline the implications of this finding for the explanatory power of social influence in the context of technology adoption and provide vantage points for further research.

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Social influence as a process of compliance

The literature review indicates that a compliance-based interpretation of social influence is the most common form. 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 (73 papers), defined as "the perceived social pressure to perform or not to perform the behavior" (Ajzen 1991, p. 188). Theoretically grounded in the theory of reasoned action (TRA; Fishbein & Ajzen 1975) and the theory of planned behavior (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. A significant positive effect was found in 73 out of 93 studies (e.g., Mardikyan et al. 2012; Titah & Barki 2009; Yang & Forney 2013). While almost 90% of the papers examined the direct effect of subjective norm on behavioral intention (e.g., Brown et al. 2010; Irani et al. 2009; Gao & Bai 2014), the remaining studies looked at its effect on actual use (Liang et al. 2010; Devaraj et al. 2008) 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 et al. 2007) and non-work contexts (Lee 2009), and regarding 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 et al. 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.

Notably, over a third of the reviewed studies (34 out of 93) 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 66% of papers (21 out of 32) found a significant social influence effect (e.g., Nysveen et al. 2005b; Sun et al. 2013; Venkatesh et al. 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 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 points 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 always operate through additional processes, they are discussed in a separate section below.

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 (70 out of 113)—in one form or another—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 et al. 2009; Hong & Kar 2006; Wang & Chou 2014). This approach was incorporated into TAM2[2] 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 this hypothesis for the voluntary context (Dickinger et al. 2008; Williams et al. 2014). However,

[2] 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).

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 a 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, Khalifa & Shen (2008), Lu et al. (2005), and Yang (2013) found evidence of even more pronounced differences in voluntary contexts, with only the internalization effect of subjective norm being confirmed, while the compliance effect remained insignificant. 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 consideration of 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[3] (Venkatesh et al. 2003), support is typically used to complement compliance-based items rather than operationalized as a standalone construct[4] (e.g., Chatterjee et al. 2015; Gupta et al. 2008). While this approach is empirically supported by sufficient levels of internal

[3] The UTAUT (Venkatesh et al. 2003) 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).

[4] 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).

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 (16% of all non-work internalization studies, but 24% of all work internationalization studies), both with regard to mandatory (Al-Gahtani 2004; Venkatesh & Zhang 2010) and voluntary adoption (Elie-Dit-Cosaque et al. 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 in the consumer sphere, where peer or family support have also been found to play influential roles in technology adoption (Thakur & Srivastava 2013; Hsieh et al. 2011).

A recent standalone representation of internalization processes on technology adoption has been developed in the form of group norms (Shen et al. 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 often been studied with regard to group action, or social technologies (5 out of 11 studies), 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 regarding IT adoption (Sarker et al. 2005; Sarker & Valacich, 2010). Analogous to the findings on social identity, the empirical results suggest that group norms are a better predictor of adoption and use behavior than subjective norm when it comes to group-based technologies (Shen et al. 2013; Shen et al. 2010; Tsai & Bagozzi 2014; Dholakia et al. 2004). 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.

Social influence as a process of identification

Thirty 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 (17 papers; e.g., Papadopoulos et al. 2013) and constructs related to image (15 papers; e.g., Williams et al. 2014).

Anchored in social psychology, 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 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 et al. 2012; Tsai & Bagozzi 2014). Almost all studies in the reviewed sample found a significantly positive effect (14 out of 16; Datta 2011; Chiu et al. 2006). Social identity was often studied in conjunction with subjective norms (8 out of 17) and group norms (7 out of 17) 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, four studies found evidence that social identity (and group norms) are better predictors of adoption and use behavior than subjective norm (Tsai & Bagozzi 2014; Shen et al. 2013; Shen et al. 2010; Bagozzi & Dholakia 2002).

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 comprises constructs relates to image (Gounaris & Koritos 2008; Chan & Lu 2004). Within IS research, the notion of image is rooted in 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 (Plouffe et al. 2001; Foon & Fah 2011) and perceived usefulness (Chan & Lu 2004; Lu et al. 2005; Williams et al. 2014). The empirical evidence supports the hypothesized relationships regarding image, while some interesting contingency effects emerge with regard to subjective norm: several studies found sustained support for the effect of image on perceived usefulness, while subjective norm 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 independently of the contingency effects compliance-based processes are subject to such as voluntariness and experience.

Multi-processual conceptualizations of social influence

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

Twenty of the reviewed studies explore social influence through the lens of (perceived) critical mass or (perceived) network externalities (Strader et al. 2007; Wattal et al. 2010).[5] The two concepts are connected, as the presence of network externalities forms and influences the concept of critical mass, which in turns affects technology adoption (Hsu & Lu 2004). The reviewed literature finds strong empirical support both for a direct effect of critical mass on behavioral intention (Sledgianowski & Kulviwat 2009; Cheng 2011) and an indirect effect, mediated by perceived usefulness (Lee 2006; Rauniar et al. 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 or her 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, about half the studies (11 out of 20) have incorporated perceived critical mass alongside subjective norm (e.g., Cheng 2011; Kim et al. 2007). While all of the empirical works among these studies were able to validate direct or indirect critical mass effects, only one found significant support for a compliance-based subjective norm effect (Van Slyke et al. 2007). Two studies did, however, find evidence of internalization effects of subjective norm (Lee 2006;

[5] 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).

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. It is worth noting that the authors of some papers categorized under "critical mass" actually employed different labels like "visibility" (Gounaris & Koritos 2008; Plouffe et al. 2001) and "descriptive norms" (Yang & Forney 2013; Yu 2012; Foon & Fah 2011).

Thirteen of the reviewed studies draw on social network configurations to study how social influence manifests itself in technology adoption. The configuration on an individual's social network is theorized to affect the information and norms that flow through said 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 et al. 2014; Sykes et al. 2009). Studies further differentiate by type of network, such as supportive versus informational (Bruque et al. 2009) or intra- versus inter-team connections (Magni et al. 2013), or 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). Most of the reviewed articles (8 out of 11) 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, six 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 institutions. Social capital has attracted a lot of research attention with sociological and organizational research (Borgatti & Foster 2003; Baker 1990; Adler & Kwon 2002), but has so far featured less prominently in technology adoption research. Thematically, social capital has been studied in relation to digital inequality (Kvasny & Keil 2006; Hsieh et al. 2011), participation in virtual (knowledge sharing) communities (Chiu et al. 2006; Wasko & Faraj 2005; Liao & Chou 2012), and in the context of tourism technology adoption (Lee et al. 2013). Conceptually, the dominant theoretical foundation is Nahapiet and Ghoshal's seminal definition of social capital as a combination of structural, relational, and cognitive dimensions (1998). Through these dimensions, the social capital construct captures compliance, internalization, and identification effects of social influence. Correspondingly, three studies have used social capital as a complement to subjective norm in order to attain a better representation of social influences (Liao & Chou 2012; Lee et al. 2013) and have found empirical support for both constructs. Extant research has validated both the construct's direct effect on use or intention to use (Hsieh et al. 2011; Chiu et al. 2006), as well as its indirect effect mediated by attitude (Liao & Chou 2012) and instrumental beliefs (Lee et al. 2013).

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 82% 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 susceptibility to contingency effects underscore this finding.

On the other hand, there exist a wide range of alternative conceptualizations of social influence that have so far not garnered as much attention in technology adoption research. This is mainly due 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 (Tsai & Bagozzi 2014; Shen et al. 2013). 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 extant plethora of social influence conceptualizations.

When 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 norm," although the underlying motivations, decision rules, and social processes differ both conceptually and theoretically (Cho 2011, p. 284; Kraut et al. 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 or she should use a new technology, the perception that others support his or her use of a new technology, and the perception that use of the technology is associated with 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 relate 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 to properly establish if and how they are interrelated.[6]

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

Structural view of social influence in technology adoption research

The literature reviewed in this paper was further categorized structurally by level of analysis. Behavioral and sociological research commonly differentiate between individual, group, organizational, and societal levels of analysis (DeLone & McLean 1992; Markus & Robey 1988; Klein et al. 1994), examples for all of which could be found in the reviewed literature (Figure 3). In addition, in some cases multiple levels of analysis could be observed, specifically combinations of individual and group levels of analysis.

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The large majority of the sampled research (99 out of 113 papers) on social influence in technology adoption has been conducted at the individual level. This in itself is not a surprising

[6] Cho (2011) provides a good example for how to do this based on subjective norm and perceived critical mass.

finding since technology adoption overall has traditionally been studied primarily at the individual level (Venkatesh et al. 2003; Delone & McLean 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 the de-facto standard methodology, some IS scholars criticized the fact 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 purely at a group, organizational, or societal level. At the group level, one group of scholars has 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 (Sarker et al. 2005; Sarker & Valacich 2010; Klein et al. 1994). Others have investigated multi-group adoption. Plouffe et al. (2001), for instance, study 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 (HIT) systems (Peng et al. 2014) as well as open source software adoption in SMEs (Macredie & Mijinyawa 2011) and found significantly positive effects. At a societal level[7], the sampled studies investigate either the applicability of technology acceptance models and social influence processes within non-Western contexts (Datta 2011; Al-Qeisi et al. 2015) or undertake cross-cultural comparisons, generally between Western and Asian cultures (Venkatesh & Zhang 2010; Choi & Geistfeld 2004; Yang et al. 2012). Given the small number of papers that fall into the purely 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.

A number of papers (12 out of 113) 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 (Tsai & Bagozzi 2014; Dholakia et al. 2004; Bagozzi & Dholakia 2006) and social-network facilitated teams (Shen et al. 2010; Shen et al. 2013). 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), in which 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.

[7] The sample of studies at the societal level is limited as 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 and Kayworth (2006).

The current state of the art presents ample opportunities for future research, particularly at the group and organizational level. At the group level, IS scholars should build on process theory and examine in greater detail how group dynamics and interactions—manifestations of social influence—affect group attitudes towards 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 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 et al. 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. 2014) and 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 intraorganizational 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).

Finally, a multilevel approach presents technology adoption researchers with the opportunity to study social influence in a way that extends beyond the focal individual's perception. This is relevant in 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 and the social referents' beliefs and behaviors.

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 were conducted at the individual level (99 out of 113 papers). 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 from 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.

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 (Wang et al. 2013; Kim et al. 2007; Venkatesh et al. 2011). Within the consumer sphere, studies explore acceptance and use of technologies such as mobile apps, e-commerce, and social media (Junglas et al. 2013; Hong et al. 2008; 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 et al. 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 et al. 2010).

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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. 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 to research on non-social technologies (15 out of 31 studies on social technologies vs. 15 out of 82 studies on non-social technologies). This includes aspects such as social identity (Shen et al. 2013; Bagozzi & Dholakia 2002), social status (Nysveen et al. 2005a; Yu 2012), and relational commitment (Li et al. 2005), all of which 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 that goes beyond social pressure is required.

With social technologies predicted to constitute an increasingly important part of organizational and consumer ICT infrastructure in the future, they provide an attractive avenue for future research. 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 fully 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 technologies 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 [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.

4.3 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, and the national or cultural origin of the respondents were reviewed.

Specification of social reference group

Social influence is a relational construct dependent on a specific social reference group. 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, p. 563). The referent influence may be interpersonal (e.g., family, friends, colleagues, superiors) or external (e.g., mass media, expert opinions). 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.

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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 2). 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, e.g., peers may think differently about the new technology than superiors. This may result in confounding effects when left unclarified.

The second cluster encompasses studies that specify one or multiple social referents within a single social influence variable (e.g., Liang et al. 2010; Neufeld et al. 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 α 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 α around 0.7 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 significantly 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 for why they found a significant social influence in one of their studies but not in 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).

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 rom 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. 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 et al. 2003). In addition, behavioral antecedents of 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).

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 (Rice et al. 1990; Fulk et al. 1990). For example, rather than asking subjects what 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 subjects' (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. 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 should consider employing direct measures of social referents' beliefs and behaviors—where meaningful—to complement and contrast self-reported survey data.

Respondent origin

A large proportion of technology adoption research is based on US-American and Chinese samples. In our literature sample in this paper, over 60% of papers draw on these populations. The remainder draws on a variety 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 et al. 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 et al. 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-American and Chinese 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, the 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.

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 by 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 have begun to incorporate additional social influence processes and conceptualizations in their research and thus introduce 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. We 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 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 (Legris et al. 2003; Bagozzi 2007). Building upon the findings of this review, we attempt 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, we propose a multidimensional view of social influence, as depicted in Figure 5. More specifically, we 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 evolves from a tool level to a social level. Finally, the interaction between technology and social referents influences the nature of social influence, i.e., whether it is supportive or dismissive. These interactions can take place at various structural levels of analysis, from individual to societal. The following paragraphs describe each proposed interaction in greater detail.

--- INSERT FIGURE 5 ABOUT HERE ---

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 (Junglas et al. 2013; Bagozzi 2007). 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 him- or herself may affect and influence the social sphere that he or she 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 et al. 1985). In line with Mason, Conrey, and Smith (2007), we propose that models seeking 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 (Mason et al. 2007).

For another, future IS research should consider the extent of interaction between users and technology. 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,” i.e., 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 other 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.

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 (Gallivan et al. 2005; Brown et al. 2010). 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. They may ask, for instance, how the social influence from a social referent who views the technology as useful but unwieldy differs from that of a social referent who views it as accessible but not that useful.

Combining all these dimensions allows us to move from disconnected views 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 from 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.

--- INSERT FIGURE 6 ABOUT HERE ---

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 3 summarizes the most promising of these by clustering them into five main categories. we 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.

--- INSERT TABLE 3 ABOUT HERE ---

The present paper is subject to limitations that provide opportunities for future research. 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.

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 neighboring 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 out 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. Is has summarized 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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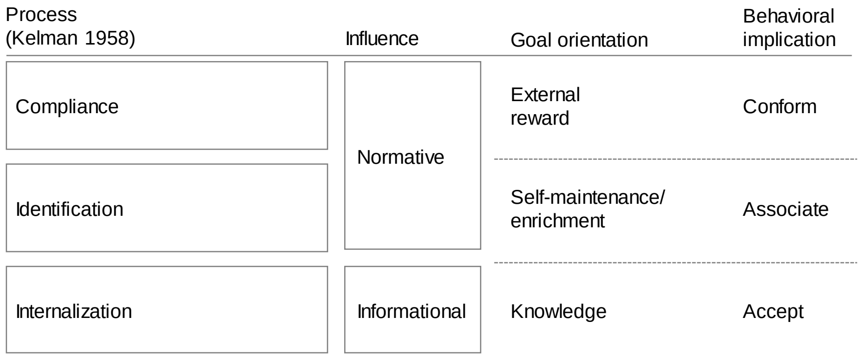

Fig. 1: Social influence processes (adapted from Burnkrant & Cousineau 1975, p. 207)

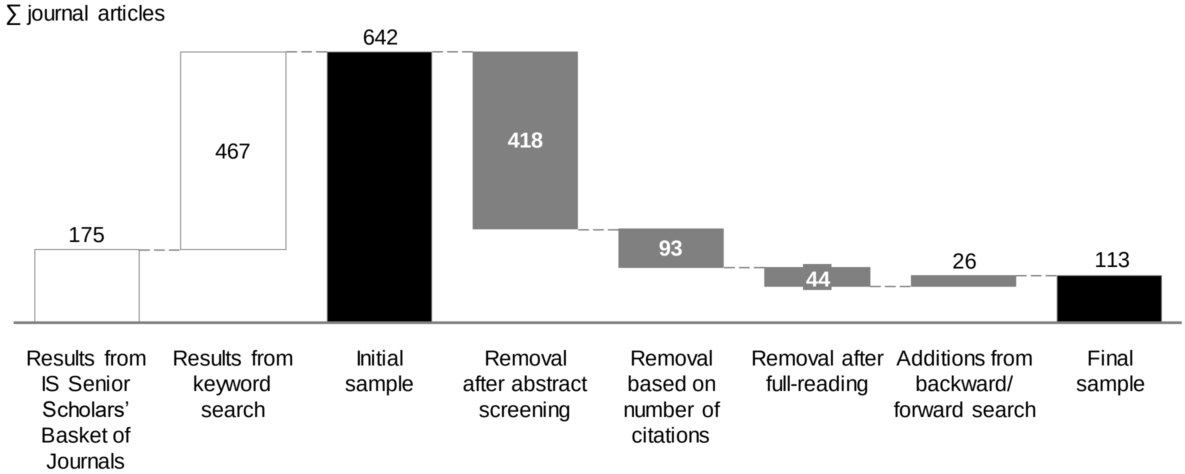

Fig. 2: Overview of article screening steps

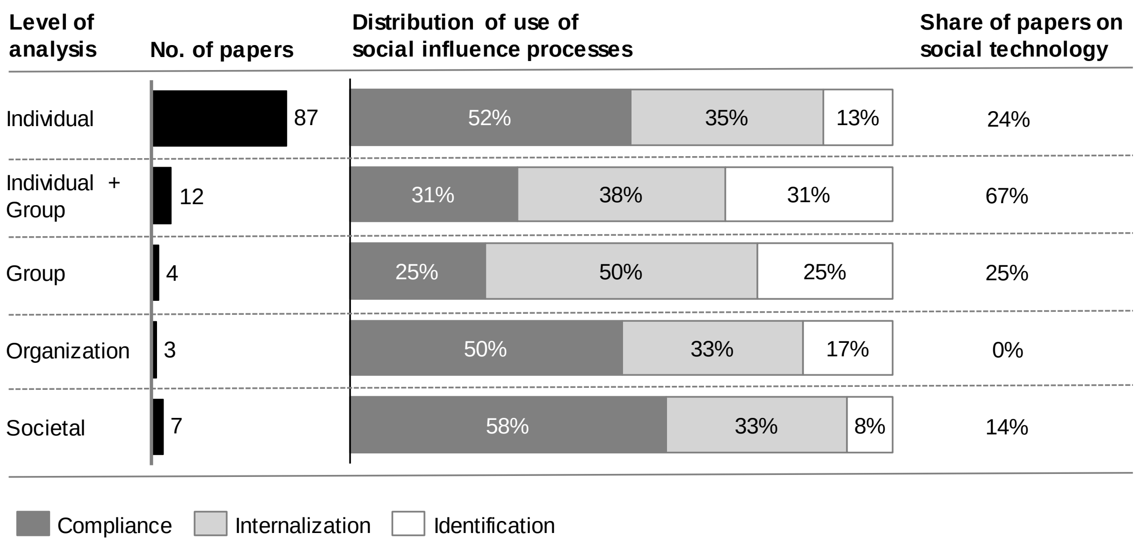

Fig. 3: Levels of analysis by social influence process and focal technology

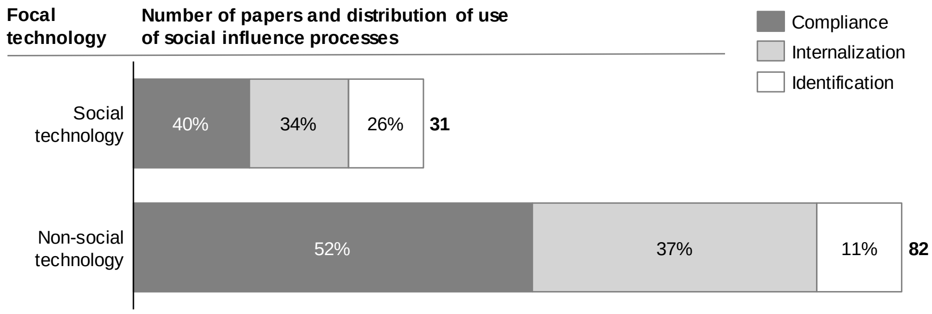

Fig. 4: Summary of focal technology by social influence process

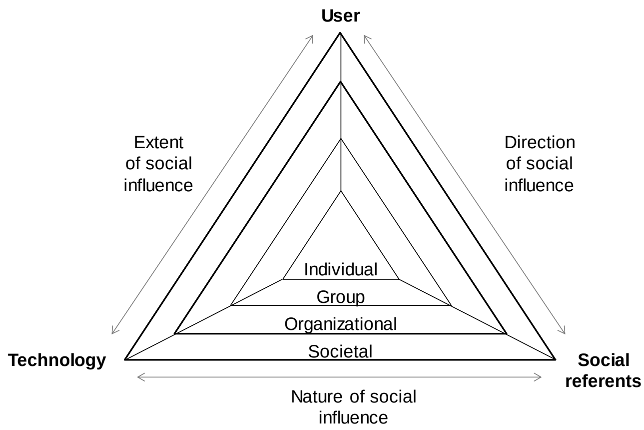

Fig. 5: Multidimensional view of social influence in technology adoption

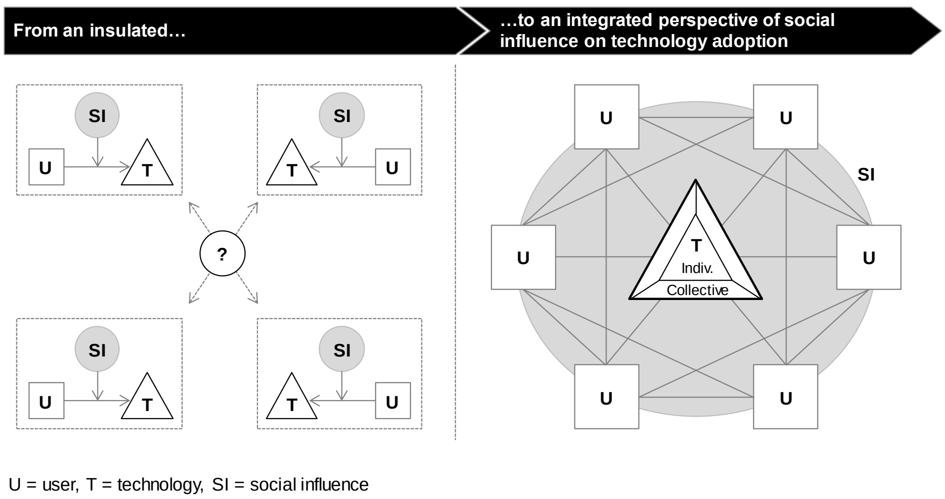

Fig. 6: Integrated perspective of social influence on technology adoption

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

Construct	Theoretical basis	Definition	# papers by social influence process[a,b] CPL	INT	ID
Subjective norm[c]	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)	**73**	**43**	17
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)	10	13	**17**
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)	11	10	**15**
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)	6	**11**	7
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)	9	**13**	2
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	**13**		4
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**		5
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 per social influence process			93	70	30

a. Some articles are counted more than once because they make use of more than one social influence construct; shaded cells indicate dominant social influence process per construct
b. CPL = compliance, INT = internalization, ID = identification
c. Also commonly referred to as social factors or social norms

Table 2: Social reference group specification in technology adoption research

Social referents	**Item wording (examples)**	**Sources (examples)**
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	*Construct A: Interpersonal influence* 1. My supervisor thinks that I should use the system 2. My colleagues think that I should use the system 3. My friends think that I should use the system *Construct B: External influence* 1. I see news reports that using the system is good 2. Expert opinions depict a positive sentiment for using the system 3. Mass media reports convince me to use the system	Brown et al. 2010; Cheng 2011; Hsieh et al. 2011; Lewis, Agarwal, & Sambamurthy 2003

Table 3: Summary of recommendations for technology adoption research

Recommendation	**Examples**
1. Pursue an integrated, multi-theoretical understanding of social influence	• Incorporate non-compliance-based social influence processes and conceptualizations • Acknowledge and leverage multi-theoretical foundation of social influence research • Further develop and validate measures of internalization and identification, e.g., group norms/social identity, in different contexts • Test how different social influence conceptualizations interact • Account for interactions between user, social referents, and technology (multi-directional social influence, social components of technology use, variance in social referents' beliefs/behaviors)
2. Move beyond the individual and explore other levels of analysis	• 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 • Consider multiple levels of analysis, particularly when studying social or collaborative technologies to achieve more proximate representations of social influence
3. Validate contingency effects	• Test variance in contingency effects for different social influence constructs and processes • Test moderating impact of focal technology, i.e., social/non-social
4. Justify use of construct measurements	• Avoid lumping together conceptually and theoretically distinct social influence constructs; test the subordinate constructs separately in order to properly establish interrelation • Bypass common method bias from survey-based, self-reported data by capturing social referents' actual beliefs/behaviors directly where meaningful • Specify social referents when operationalizing social influence to account for variance among referents
5. Employ more diverse samples and longitudinal studies	• Utilize more non-US and non-Chinese sample populations • Greater focus on technologically emergent markets such as Africa, the Middle East, Africa, and Asia (excl. China) • Conduct more longitudinal studies to investigate the sustained effects of social influence over time or regarding continued use