DOES SOCIAL MEDIA ENHANCE SOCIAL CONNECTIVITY OF AN AGING POPULATION?:
WHY RESEARCH IS INCONCLUSIVE AND WHAT TO DO ABOUT IT
Research in Progress

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Abstract

In today’s aging world social media are often viewed as a means to enhance social connectivity of older adults. However, previous research on social media’s influence on social connectivity yields conflicting results and fails to assess the –debatable- causal direction of relationship. This research-in-progress paper suggests remedies that may yield more robust results. We propose that conflicting results may be caused by 1) the application of methods that are ill-equipped to assess causality, and 2) varying assumptions about What is adopted by Whom, How, When, and Where. We address this variation by offering four hypotheses on the social media adoption assumptions. Based on a longitudinal data set of 302 rural older adults, one hypothesis related to Where, i.e. on which geographical level, social media influences social connectivity was tested. Preliminary results show that older adults differentiate between their social connectivity at the village and neighborhood level. However, on neither of these levels significant impact of social media adoption on social connectivity was found. These results provide ground for future research on how older adults’ social media adoption affects social connectivity at different geographical levels.

Keywords: Aging, Social media, Social connectivity, Older adults, Causality, Geographical levels
1 Introduction

In today’s aging world (United Nations, 2002) social media are often believed to enhance social connectivity of isolated older adults (e.g. Ambient Assisted Living (AAL), 2012). Social media are “a group of Internet-based applications that […] that allow the creation and exchange of user generated content” (Kaplan and Haenlein 2009, p. 61). It is expected that as social media enable interactions between persons, these applications may enhance social connectivity, i.e., an “individual’s perception of the interpersonal relationships and social roles in their life” (WHOQOL group, 1995, p.1405). Nevertheless, evidence to support this argument is lacking. Most studies have not taken into account older populations, and focused on student populations (Steinfield et al. 2012). Dynamics in older adults adoption and social connectivity patterns are likely to differ between older adults and students. The digital divide literature for example shows that older adults are often later to adopt new technology (Czaja et al. 2006; Morrell et al. 2000; Morris and Venkatesh 2000).

Moreover, the causal direction of the relationship between social media and social connectivity is debated (Wagner et al., 2010; Dickinson and Gregor, 2006). The direction of this assumed causality has important consequences for future research as well as policy decisions. First, in case of a ‘causal’ relationship, i.e. social media use enhancing social connectivity, researchers may want to study how to optimize this effect and how social media change social norms. Policy measures can then aim at stimulating social media adoption among particular groups of interest, such as older adults, to reduce possible loneliness (Dykstra, 2009) and stimulate independence (Peeters et al., 2013). Second, in case of ‘reversed causality’, i.e. the socially connected are more likely to adopt social media, research and policy attempts to stimulating social media adoption to enhance social connectivity would be fruitless. Instead, a critical assessment of the digital divide (e.g. Agarwal et al., 2009) would be appropriate. Ultimately, causality may work in both directions, indicating that the socially connected are more likely to adopt social media, which in turn further enhances their social connectivity. In that case, social media adoption will ironically lead to even sharper digital divides. Tackling these divides that will most probably be socio-economic in nature (Hage et al., 2013), requires a less straightforward set of policy measures than promoting social media adoption. Considering this societal relevance of the direction of causality, the calls to (more rigorously) test causality between social media adoption and social connectivity are unsurprising (Park, 2011; Wagner et al., 2010; Steinfield et al., 2008; Dickinson and Gregor, 2006).

Apart from the direction of causality, the net effect of social media adoption is also ambiguous. Theoretical arguments have been developed for both positive (Steinfield et al., 2008; Ellison et al., 2007; Lampe et al., 2006) and negative (Dickinson and Gregor, 2006; Nie, 2001; Kraut, 1998) effects on social connectivity. Especially among older adults social connectivity outcomes seem not straightforward (Xie, 2007). Older populations thus require further research, especially as thus far most studies on social media and social connectivity focused on national or student populations (Steinfield et al., 2012). Finally, social connectivity at the local level seems affected differently by social media than at other geographical levels (Hampton et al. 2011; Hampton et al. 2009). As older adults are dependent on their local network for physical support and care, these puzzling findings deserve further investigation. Sharper distinctions of the level(s) at which social media adoption influences social connectivity are required.

The main question of our larger research project: ‘Can social media enhance social connectivity of an aging population?’ thus remains unresolved. In this research-in-progress paper we make steps to formulate an answer. In order to better understand the consequences of social media adoption in older adults’ lives, we seek to answer the following questions: 1) Why do studies focusing on social
connectivity outcomes of social media adoption yield conflicting results? and 2) What are remedies to ensure that future research will produce more robust results? This paper contributes to the literature by addressing these questions, through a critical discussion of the available evidence for the causality direction. We also develop four hypotheses for further research and - as a first step - test one of these. Results underline the relevance of studying outcomes of social media adoption at specific geographical levels of social connectivity.

1.1 Conflicting results (RQ1)

Within the Information Systems (IS) field in general, literature on causality is sparse (Gregor and Hovorka 2011; Mithas et al., 2009; Gregor, 2006; Lee et al., 1997; Markus and Robey, 1988). Causality has thus been referred to as ‘the elephant in the room in information systems epistemology’ (Gregor and Hovorka, 2011). What is true for the IS field in general also holds for studies on internet or social media use and social connectivity (Park 2011; DiMaggio et al 2001). Here, cross-sectional data or statistical techniques that are ill-equipped to establish causality are often applied to ‘show’ the effects of social media adoption on social connectivity (e.g. Hampton et al., 2011; Valenzuela et al., 2009; Vergeer and Pelzer, 2009; Valkenburg and Peter, 2007). In these studies relationships are shown, but the direction of causality is deduced and not based on empirical evidence. Deduction is remarkable as the theoretical argument can be made both ways.

On the one hand, social media use may extend or enhance the existing social network, because it lowers the barriers for forming relationships with others (Ellison et al., 2007; Steinfield et al., 2008). Moreover, social media may play an important role in maintaining pre-existing offline relationships (Lampe et al., 2006). On the other hand, recent work suggests the reversed relationship: i.e. peer influence renders people with a large social network more prone to adopt information and communication technology (ICT) (Chen, 2013; Ward, 2012; Agarwal et al., 2009). Both Agarwal and her colleagues (2009) and Ward (2012) focus on spill overs in geographic regions to show that the higher the share of adopters in a region, the more likely an individual is to also adopt. This is referred to as peer influence. The relationship is especially strong for those that are well socially connected (Agarwal et al., 2009). The two theoretical arguments fuelled Park’s (2011), Steinfield et al.’s (2008), Dickinson and Gregor’s (2006) and Wagner et al.’s (2010) call for a more explicit examination of the causality between social media adoption and social connectivity and in particular to develop better methods to determine causality.

Developing better methods is relevant as also longitudinal studies on the topic (Bandtzæg 2012; Burke et al., 2011; Park, 2011; Valkenburg and Peter, 2009; Miyata and Kobayashi, 2008; Steinfield et al., 2008; Hampton, 2007; Lampe et al., 2006) were not always able to test causality and yielded conflicting results. Whereas Steinfield et al. (2008) and Burke et al. (2011) found proof that Facebook use increases weak ties; Brandtzæg (2012) did not find such a relationship. Moreover, Valkenburg and Peter (2009) find a relationship between quality of offline friendships and instant messaging, whereas Brandtzæg (2012) and Park (2011) only find a positive relationship between use and the number of social ties. It seems that longitudinal data are no panacea when assessing the relationships between social media and social connectivity. A more careful assessment of causality is required. This Research in Progress-paper provides a way forward.

1.2 Remedies (RQ2)

As explained above even longitudinal studies on the relation between social media adoption and social connectivity have yielded conflicting results. In addition to ill-assessments of causality, the
explanation may lie in the assumptions underlying the studies related to what is used how by whom (also noted by Burke et al., 2011; Park, 2011) when and where. Here, we address these assumptions and formulate four hypotheses that may direct further research on the topic. The four hypotheses are not unrelated; their underlying thought is that both social media and social connectivity are multidimensional.

First, **What** is adopted may affect social connectivity outcomes. Miyata and Kobayashi (2008), for example, show that PC e-mailing enhances network diversity whereas using the seemingly similar mobile phone e-mail application does not. Therefore, when studying a particular social media application, caution is required in generalizing results to other social media applications.

Second, **How** the application is used influences outcomes. For example, Burke et al. (2011; 2010) find that correlations with social connectivity estimates differ between Facebook users that actively communicate with others through Facebook and users that passively ‘consume’ information posted on walls. Valkenburg and Peter (2009) find the positive effect of using instant messaging on the quality of offline friendships to be completely explained by disclosure of information online, i.e. the particular way of use. Also Brandtzæg (2012) finds different social connectivity outcomes for different user types: Whereas ‘Debaters’ and ‘Advanced’ user types saw their numbers of acquaintances increase over time, the other user groups included did not. Thus, researchers should differentiate between different types of use, for example social and non-social use (Zhao, 2006; Steinfield et al., 2012). We hypothesize that:

**H1:** The type of social media adoption affects social connectivity outcomes, whereby adoption of social functionalities has a stronger effect on social connectivity than informative functionality adoption.

Third, **Who** is communicating seems to make a difference. Hampton (2007) found that those with little initial contact with neighbors did not increase their number of neighborhood contacts after adoption of a neighborhood e-mail list, whereas adopters who regularly participated in their community did see an increase in their numbers of contacts after adoption. More over Burke et al. (2011) find that initial communication skills and self-esteem influence social connectivity outcomes. These findings suggest that initial social connectivity moderates the effect of social media adoption on subsequent social connectivity. This digital divide effect leads to our second hypothesis.

**H2:** Social connectivity of social media adopters with high initial social connectivity increases more than the social connectivity of social media adopters with a low initial social connectivity.

Fourth, Hampton (2007) also found that initially, early adopters of a neighborhood e-mailing list had smaller social networks than late adopters, but these networks grew over time, whereas the social networks of late adopters declined. A possible explanation may be that early adopters differed from late(r) adopters in terms of initial social connectivity. That is, they may differ in the way that early adopters and late adopters start using social media for different reasons, which in turn would affect social connectivity outcomes. Antoci et al. (2013, 2012) present a model that provides a rationale for this. They find that, in a situation of time pressure, the larger the share of a population that adopted social network applications, the greater the network value and thus the social benefit of adopting the social network application. These findings suggest that later in the application life cycle the incentive structure to adopt changes to adopt increases. We suggest that **When** the technology is adopted, i.e. the timing of adoption, affects the social connectivity outcomes. Following Hampton (2007), we expect that initial local social connectivity of early adopters is lower than that of late or non-adopters. However, after adoption early adopters experience a sharper increase in social connectivity.
than late and non-adopters (H3a). Based on the Antoci et al. (2013, 2012) models we expect that local social connectivity levels of non-adopters eventually decline as a larger share of the total population adopted (and thus communicates via) social media (H3b&c). Zooming in on one group of traditionally late and non-adopters, i.e. older adults, it has been suggested that especially among older adults increases in social connectivity after social media adoption, may be due to ICT course participation rather than social media adoption itself (Dickinson and Gregor, 2009; Xie, 2007). We hypothesize the following:

**H3a:** Early adopters experience a sharper increase in social connectivity over time than late and non-adopters.

**H3b:** Late adopters experience a sharper increase in social connectivity than non-adopters.

**H3c:** Non-adopters experience a decrease in social connectivity after later adopters’ adoption.

Fifth, to Where, i.e. on which geographical level, is communicated through the application may alter results. Hampton et al. (2011) show that although social networking sites enhance general network diversity, they have a negative effect on neighborhood ties, i.e. the most local geographical level. Also Hampton (2009) finds that social network users are less likely to ask their neighbors for help. The studies of Hampton suggest social media adoption may influence social connectivity differently depending on the geographical level. We therefore hypothesize the following:

**H4:** Local forms of social connectivity are negatively affected by social media adoption.

The conceptual model including all hypotheses is presented in figure 1. In the remaining of this paper, we test one of these hypotheses, hypothesis 4. Hypothesis 4 is related to the geographical level at which social connectivity of older adults is influenced by social media adoption. Despite calls to study late social media adoption among older adults (e.g. Xie, 2007), so far most studies on the relationship between social media and social connectivity focused on student or youth populations (Steinfield et al., 2012). This study will therefore explicitly focus on older adults. In later work, we aim to also test the other three hypotheses developed above. The initial analysis below is based on social media adoption.

![Figure 1. Conceptual model](image)

**2 Methods**

**The dataset:** For this study the entire 65+ population of the four small villages (with a population below 600) within one of the Dutch provinces was invited to participate in an annual survey, in total 332 people were approached in 2011 (t0) and 381 in 2012 (t1). Surveys were distributed by local volunteers and if possible personally handed over. After a few weeks non-respondents were approached again. This approach resulted in relatively high response levels: 62% (t0), 70% (t1). For this study we used a long dataset in which each completed survey was entered as a new case. In total 302 participants filled out one or two questionnaires, 165 of which filled out the questionnaire both
at t0 and t1, yielding a total of 467 cases. Despite high response levels, systematic differences between respondents and non-respondents may cause biases in the results. To account for this we compared the village, gender and age (proxy for health) between respondents and non-respondents using the Chi-square test (see table 1). We see that slightly more females filled out the survey, though this results is only significant at the 0.1 level. The survey contained questions on social connectivity, Internet and social media use, socio-economic status estimated through education level, family composition, health status, age and gender.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Test</th>
<th>Value (df)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (526)</td>
<td>Continuity correction</td>
<td>5.935* (1)</td>
</tr>
<tr>
<td>Age (n=388)</td>
<td>Pearson Chi-Square (minimum expected count is 32.85)</td>
<td>4.775 (3)</td>
</tr>
<tr>
<td>Village (n=526)</td>
<td>Pearson Chi-Square (minimum expected count is 19.21)</td>
<td>3.052 (3)</td>
</tr>
</tbody>
</table>

* p <0.1, **

Table 1. Chi-Square test for independence comparing respondents and non-respondents

Data analysis: The analysis was conducted in two steps. First, in order to assess at which geographical levels social media adoption may influence social connectivity a principal component analysis (PCA, Oblimin, recommended by Stevens, 1996) was conducted. Thus we followed Wagner et al.’s (2010) suggestion that existing scales may not always be appropriate for older adults. Second, based on the outcomes of the PCA, a difference-in-difference estimation (DD-estimation) was conducted. A DD-estimation is well equipped to assess causality, as it is a form of linear regression based on longitudinal data that assesses the causal effect of a particular treatment on a group (Wooldridge, 2007). It compares changes in the dependent variable (here village connectivity and neighborhood connectivity) between two points in time (t0 and t1) for a group that got treated (i.e. late adopters of social media, adoption between t0 and t1), a control group that did not get treated (i.e. non-adopters). Social media adoption was defined as respondents that at t0 had never used a computer, adopted in between t0-1 and had used either e-mail or Facebook during the last week at t1. The social connectivity is constructed through a principal component analysis (PCA).

3 Results

Principal component analysis (PCA): The sample size of the data in the PCA is well above the minimal norm of Tabachnock and Fidel (2007) and the number of included social connectivity related items (n=11) well below Nunnally’s (1978) relatively strict participant/item ratio (10:1). As common with the PCA, we selected only those components with an eigenvalue >1 and passed the Catell’s (1966) scree and parallel analysis test. Moreover, we excluded variables with a communality below 0.3. The two components that remained after these procedures (table 2) have a sufficiently high Kaiser-Meyer-Olkin score of 0.696 and shows significant results on the Bartlett’s test (P<0.001). Oblique (correlated) factor solution via Direct Oblimin is not too high (0,151). Together the components explain 55.9% of the variation. This is a little below the minimum of 60% suggested by Hair et al. (2009). However, the results make theoretical sense as a village level and a neighborhood level component can be identified.

Results indicate that participants living in small villages make a distinction between social connectivity at the neighborhood and village level. Additional data is required to construct measures of social connectivity at the regional and global geographical levels. The effect of social media adoption on social connectivity or vice versa may differ between neighborhood and village or local and regional/global geographical levels.
Testing causality using DD-estimation: The DD-estimation was conducted for both village and neighborhood connectivity. For each level of connectivity, in the linear regression model 1 we entered the control variables age, gender, education, general health status and family composition. In model 2 we then also included the independent variables in the form of treatment variables, i.e. a late adopters dummy (adopted between 2011 and 2012), an additional dummy for early adoption (before 2011), a dummy for the year of measurement (2011 and 2012), and an interaction effect between year and treatment.

For village connectivity, the explained variance ($R^2$) in model 1 is 9.0% and in model 2 11.5%. For neighborhood connectivity, model 1 explains 5.1% and model 2 6.8%. For village connectivity both models 1 and 2 are significant. However model 2 does not significantly increase the explanatory value of the model. This means that the control variables that have a significant impact on village connectivity, but not social media adoption. Women have on average a slightly higher village connectivity than men. Moreover, those with higher education have lower village connectivity. For neighborhood connectivity neither model 1 or 2 are significant. These results (table 3) support the conceptual difference between village and neighborhood connectivity even in very small rural villages (population < 600), and suggest there may also be a functional difference.

### Table 3. DD-estimation coefficients village and neighborhood connectivity

<table>
<thead>
<tr>
<th>Model</th>
<th>Village connectivity</th>
<th></th>
<th>Neighborhood connectivity</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B (SE)</td>
<td>Beta</td>
<td>B (SE)</td>
<td>Beta</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a)</td>
<td>0.115 (0.602)</td>
<td>-0.631 (0.611)</td>
<td>0.043 (0.188)</td>
<td>0.021</td>
</tr>
<tr>
<td>Gender (male=1, female=2)</td>
<td>0.272 (0.185)</td>
<td>0.136</td>
<td>0.022</td>
<td>0.042</td>
</tr>
<tr>
<td>Age (4 categories)</td>
<td>0.02 (0.095)</td>
<td>-0.353* (0.141)</td>
<td>0.044 (0.143)</td>
<td>0.031</td>
</tr>
<tr>
<td>Education (3 categories)</td>
<td>0.248</td>
<td>0.03</td>
<td>-0.363 (0.221)</td>
<td>-0.161</td>
</tr>
<tr>
<td>Living alone (=1)</td>
<td>-0.069 (0.217)</td>
<td>-0.03</td>
<td>-0.37 (0.221)</td>
<td>-0.161</td>
</tr>
<tr>
<td>Health (5 categories)</td>
<td>0.033 (0.093)</td>
<td>0.033</td>
<td>0.158* (0.095)</td>
<td>0.159</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a)</td>
<td>0.767 (0.707)</td>
<td>-1.115 (0.721)</td>
<td>0.017</td>
<td>-0.032 (0.198)</td>
</tr>
<tr>
<td>Gender (male=1, female=2)</td>
<td>0.354* (0.194)</td>
<td>0.177</td>
<td>-0.352 (0.198)</td>
<td>-0.016</td>
</tr>
<tr>
<td>Age (4 categories)</td>
<td>-0.073 (0.11)</td>
<td>-0.08</td>
<td>0.117 (0.112)</td>
<td>0.129</td>
</tr>
<tr>
<td>Education (3 categories)</td>
<td>-0.464** (0.156)</td>
<td>-0.326</td>
<td>0.136 (0.159)</td>
<td>0.096</td>
</tr>
<tr>
<td>Living alone (=1)</td>
<td>0.121 (0.245)</td>
<td>0.053</td>
<td>-0.518* (0.25)</td>
<td>-0.23</td>
</tr>
<tr>
<td>Health (5 categories)</td>
<td>0.051 (0.094)</td>
<td>0.051</td>
<td>0.15 (0.096)</td>
<td>0.151</td>
</tr>
<tr>
<td>Social media adoption (=1)</td>
<td>-1.872* (1.11)</td>
<td>-0.503</td>
<td>1.533 (1.132)</td>
<td>0.415</td>
</tr>
<tr>
<td>Year =2012</td>
<td>-0.712* (0.409)</td>
<td>-0.352</td>
<td>0.455 (0.417)</td>
<td>0.226</td>
</tr>
<tr>
<td>Social media adoption x (Year = 2012)</td>
<td>1.745 (1.134)</td>
<td>0.339</td>
<td>-1.339 (1.156)</td>
<td>-0.261</td>
</tr>
</tbody>
</table>

* p<0.1; ** p<0.01; *** p<0.001

4 Discussion and conclusion

In this study we addressed the following questions: 1) Why do studies focusing on social connectivity outcomes of social media adoption yield conflicting results with regard to causality?
and 2) What are remedies to ensure that future research yields more robust results? Evidence for the causal effect of social media adoption on social connectivity is limited. More importantly, a better assessment of causality is necessary, as some longitudinal and instrumental studies have shown a reversed causal relationship, i.e. the socially connected being more likely to adopt social media. To guide such research, four hypotheses addressing the What, How, Who, When, and Where of social media adoption were offered. Based on a longitudinal dataset including 302 older adults living in rural areas, we conducted an initial analysis of one of these hypotheses that addresses the geographical level at which social media adoption influences social connectivity.

Through principal component analyses we derived two local social connectivity components: village and neighborhood connectivity. The first component is related to social connectivity on the village level, such as participation in village events. The second component refers to social connectivity on the neighborhood level, including knowing your neighbors. Through a difference-in-difference (DD-)estimation the causal relationship between social media adoption and social connectivity was assessed. Although both village and neighborhood connectivity were not significantly influenced by social media adoption, the different relationships with control variables between the two connectivity types underline the conceptual differences between village and neighborhood connectivity. It may be that even with in small villages (N<600), inhabitants experience social connectivity differently depending on the geographical level on which social connectivity is measured.

Additional analyses not presented here, show that when interaction effects between different social media (i.e. Facebook and e-mail, the most popular social media) and initial social connectivity are taken into account, social connectivity is impacted by social media adoption. The influence of the control variables changes, and again the results differ for village and neighborhood connectivity. This suggests that social media enabled social connectivity research should differentiate between social connectivity at various geographical levels.

In order to further develop our study, we plan to test all four hypotheses developed. For a robust assessment of the causal relationships a third survey round is required, which will be conducted in Spring 2014. By then, the dataset will include adoption behaviors of older adults from four rural villages over a three-year period. Moreover, it will include detailed, longitudinal information on different types of social media adoption. An extended time horizon with repeated measurements and more detailed information on social media adoption allows a careful analysis of social media adoption’s influence on social connectivity at different geographical levels. We hope the study will shed new light on how innovations in social media impact our social lives at different geographical levels.

To conclude, longitudinal research and robust analysis of the causal direction of relationships at different types of social connectivity is crucial for distinguishing between social media enabled social connectivity and social connectivity enabled social media adoption. This study shows that the relationship between social media adoption and social connectivity may be more complex than assumed in most studies. The model of Antoci et al. (2013, 2012) as well as local studies by Hampton (2007) and Hampton et al. (2011) offer important insights for further research directions outlined in this paper. Future research will need to differentiate between different geographical levels of social connectivity. This will help to better understand how social media may change affiliations and interactions between people. From a praxis perspective, social media adoption research among older adults is especially relevant because aging societies are confronted with increasing health care costs. These investigations will help to assess how social media can be used to reduce these costs, while maintaining or enhancing older adults’ wellbeing.
References


