Understanding differentiated Internet use in older adults: A study of informational, social, and instrumental online activities

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Abstract. Internet use is becoming increasingly important for the daily lives of older adults. Simultaneously, the range of online activities is also broadening. However, previous research in technology adoption mainly focuses on Internet use in general, and only few studies pay attention to various online activities that older adults engage in. Exploration of factors explaining specific online activities is still limited. To bridge this gap, we examined the role of socio-demographic characteristics and perceived behavioral control (PBC) in predicting informational, social, and instrumental online activities in a sample of 1,222 participants (age 65+). Our results show that those who were younger, with higher education, and with higher PBC were more likely to perform all online activities, while men had higher odds than women of performing informational and instrumental but not social online activities. Cultural participation was a positive predictor for all online activities except online banking. For informational online activities, the effect of PBC was moderated such that it was weaker for those with higher education. Based on our empirical results, we contribute to the literature a nuanced understanding of older adults' Internet use.

Keywords: *IT, Older Adults, Online Activities, Survey*

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1. Introduction

Internet use in older adults is rising around the globe. This age group is often defined through the transition from working life to retirement, which happens around the age of 65 in many industrial countries. The past ten years have witnessed tremendous changes in the frequency of Internet use, and this development is ongoing. For instance, the share of Americans age 65+ being online has increased from 28% in 2005 to 67% in 2016 (Anderson and Perrin 2017). Engagement with the Internet has become important for the daily lives of many older adults. Internet use can facilitate their social ties, leisure activities, and consumer behavior (van Boekel et al. 2017; Vroman et al. 2015). Given that deteriorating health often impairs older adults, Internet services can assist in mitigating some of the inevitable consequences of aging. For instance, being online can help prevent isolation and reduce the feeling of loneliness (Chopik 2016; Khosravi et al. 2016). Therefore, Internet services provide opportunities for older adults to pursue an active and self-determined lifestyle.

Concurrent to the increase of Internet use in older adults, the range of activities performed online has changed dramatically. In the past, the main online activities were surfing the web and e-mailing (Fox 2004). Recent studies show that older adults use the Internet for a broadening range of activities, which includes for instance, social networking and shopping (van Deursen and Helsper 2015; Vroman et al. 2015). This development has been amplified by user-friendly and affordable apps and devices (e.g., smartphone, tablet computer).

In light of the changes in older adults' Internet use, understanding of their differentiated online activities is limited. While only few studies have investigated particular online activities (Hunsaker and Hargittai 2018), many studies are concerned with Internet use in general (Keränen et al. 2017; Seifert et al. 2017; Siren and Knudsen 2017). Other studies ask for several online activities but then aggregate them into a composite variable (Chopik et al. 2017; Macedo 2017). Some studies investigate a single online activity such as shopping (Lian and Yen 2014), or a set of topic-related activities such as health (Hong and Cho 2016). The findings from these studies cannot necessarily be generalized to other online activities. Only a few studies present results for a broader set of online activities (Choi and DiNitto 2013; Gell et al. 2013; Nimrod 2018; Van Deursen and Helpser 2015). However, their regression models exhibit rather low explanatory power, or explained variance has not been reported at all.

Collectively, prior research either does not take into account the enhanced diversity in online activities performed by older adults, or lacks in explanatory power. Our study seeks to fill this gap in the literature by considering older adults' favorite online activities, and integrating perceived behavior control (PBC) into a digital divide model. PBC refers to one's perceptions of their ability to exhibit a given behavior (Ajzen 1991), and is an important predictor of actual behavior. Our approach draws upon the digital divide literature, which examines inequalities in use of information technology (IT) based on socio-demographics (e.g., age, gender, and education) (van Dijk 2005; Warschauer 2004). This focus is different from theories of technology acceptance, which put emphasis on psychometric characteristics (Davis et al. 1989; Venkatesh and Davis 2000). Prior research has begun integrating socio-demographic characteristics into such theories. For instance, the Unified Theory of Acceptance and Use of Technology (UTAUT) includes gender and age as moderators of PBC (Venkatesh et al. 2003). Adaptations of UTAUT in the context of older adults have integrated education (Choudrie et al. 2018; Macedo 2017; Niehaves & Plattfaut 2014). While these adaptations enhanced the explanatory power, we expect similar improvements when we apply a digital divide perspective.

The objectives of our study are to: (1) develop a digital divide model including PBC to explain older adults' online activities and (2) empirically validate our propositions for six online activities using survey data (*N* = 1,222), which we collected in May 2017 in Germany. We examine three types of online activities, namely informational (i.e., searching the web, viewing pictures/videos), social (i.e., writing e-mails, writing comments/reviews), and instrumental online activities (i.e., banking, shopping), which are most prevalent in older adults (Anderson and Perrin 2017).

2. Literature Review and Hypotheses

2.1 Prior Research

Use of IT by older adults, and in particular Internet use, is a vibrant field of research, characterized by multi-disciplinary approaches (Hunsaker and Hargittai 2018). Much of the literature focuses on Internet use in general, highlighting differences between, for instance, older and younger, men and women, low and high educated. Other studies examine the negative impact of specific health conditions such as frailty on Internet use (Keränen et al. 2017). Further studies demonstrate the importance of psychological characteristics, e.g., showing that Internet use increases with higher levels of subjective norm (Pan and Jordan-Marsh 2010). Socio-economic characteristics such as income have also been identified to positively predict Internet use (Hargittai and Dobransky 2017). While prior research makes clear these factors matter for older adults' Internet use, limited research has examined the role of such factors in explaining differentiated online activities (Hunsaker and Hargittai 2018).

Research has already acknowledged the increasing diversity of older adults' Internet use, and therefore, administered measurement instruments that include various online activities. The purpose of such instruments is to enhance precision of the construct Internet use; hence, researchers ask participants about their online activities and then aggregate answers into a composite variable. For example, Chopik et al. (2017) measure Internet use by asking about engagement in ten activities and devices (e.g., e-mail, skype, smartphone), and then sum up the yes/no answers to an overall Internet use score. Similarly, Hargittai and Dobransky (2017) report on two studies examining five and six online activities, respectively. In each study, the individual answers (yes/no) were aggregated into a composite variable. In summary, these studies use advanced measurement instruments, however, they do not contribute to a nuanced understanding of online activities.

The first step in enhancing the understanding of older adults' online activities is studying a particular activity or a set of topic-related activities. For instance, Hong and Cho (2017) examine four health-related online activities, namely, seeking health information, buying medicine, connecting with people with similar health problems, and communicating with doctors in the past 12 months (yes/no). In their longitudinal study of Americans aged 55+, they find that younger age, better education, and higher income only enhanced the probability of using the Internet for seeking health information but not for the other activities. By uncovering important differences of predictors, even among related activities, the study by Hong and Cho (2017) underscores the need for a nuanced understanding of specific online activities.

The next step is to examine a much broader range of online activities that older adults engage in. Only a few studies follow this approach. In the study by van Deursen and Helsper (2015), participants were asked about engagement in 23 online activities on a five-point frequency scale (ranging from "never" to "almost daily"). These activities were clustered into eight categories: music and video, shopping, news, information, email, health services, social entertainment, and civic services. Then, mean frequency per category was calculated. Van Deursen and Helsper (2015) find that three socio-demographic characteristics only lead to higher use for a subset of activity types, i.e., being men (4), younger (3), and higher educated (1). Choi and DiNitto (2013) analyze secondary data from the National Health and Aging Trends Study (NHATS) and consider three types of online activities (health-related tasks, shopping/banking, and e-mail/texting). By using logistic regression analyses, they find contingency upon the type of online activity for several socio-demographic characteristics including age (negative), race/ethnicity (lower odds for minorities), and living arrangement (higher odds for living with a spouse). The study by Gell et al. (2013) also uses data from the NHATS to investigate patterns of technology use. Participants were asked whether they had used the Internet for four health-related Internet tasks in the past (e.g., communication with health care provider). Participants also reported whether they had the used the Internet for five personal tasks (e.g., banking, shopping). The responses (yes/no) were used to derive two dichotomous variables for health-related and personal tasks, respectively. Gell et al. (2013) find that technology use varied significantly by socio-demographics and health status and that reasons for use differed by type of disability and activity-limiting impairments. A recent study by Nimrod (2018) defines four groups of online activities, i.e., native activities, old media, interpersonal communication, and entertainment, with each group including two to four specific activities, e.g., entertainment includes online games and watching TV. Nimrod (2018) finds that socio-demographics only enhanced the probability of use for some activity groups, e.g., being men (old media, interpersonal communication), having a partner (old media), higher education (old media), and higher income (entertainment).

The results of prior studies demonstrate the urgent need for exploring differentiated online activities. However, the regression models developed by van Deursen and Helsper (2015) and Nimrod (2018) exhibit rather low explanatory power (ranging between 2% and 13%), while explained variance in online activity is not available from the studies by Choi and DiNitto (2013) and Gell et al. (2013). Moreover, Gell et al. (2013) do not report regression results for socio-demographic characteristics except for health conditions. In addition, interpreting the results of Nimrod (2018) should take into account that the scales defined for the four groups of online activities have low levels of internal consistency, with Cronbach's alpha for each group below the common threshold of 0.7 for acceptable consistency. Hence, their aggregation of specific online activities into four groups lacks validity.

Collectively, our discussion of prior research highlights a critical gap in the literature concerning the understanding of differentiated online activities in older adults.

2.2 Hypotheses

In developing our proposition, we draw on van Dijk's resources and appropriation theory (van Dijk 2005; van Dijk 2006). This theory of the digital divide posits that categorical inequalities in society lead to unequal distribution of resources, which then causes unequal access to digital technologies. The theory describes a mechanism explaining individual differences in the use of digital technologies; therefore, it is adequate for studying older adults' Internet use (Friemel 2016; Hargittai et al. 2018). The notion of categorical inequality represents that inequality is a matter of differences between groups of people and not of individual attributes. The most frequent categories relate to age, gender, education, labor position, and personality. Belonging to certain categories determines the quantity and quality of resources available to an individual. These resources are required and conducive for using technology. For instance, older adults need to have material resources (e.g., computer with Internet access) and mental resources (e.g., openness towards the Internet), and may benefit from social resources (e.g., social support in using the Internet).

While van Dijk's theory relies upon categories, thus socio-demographic characteristics, as the root of explanation, our approach incorporates these categories and integrates PBC as a particular mental resource. In theories of technology acceptance research, perceived behavioral control has been found important for explaining actual IT use (Venkatesh et al. 2003). PBC is within UTAUT the only predictor that has a direct influence on actual IT use and is not fully mediated by intention to use. Note that the role of socio-demographics has also been acknowledged in the technology acceptance literature, and led to adaptations of prior theories (Venkatesh et al. 2016). Next, we present the hypotheses on socio-demographic characteristics, followed by the hypotheses on PBC.

Gender is an essential categorical inequality in digital divide research, leading to the men category dominating the women category. Gender differences in resources are not due to biological gender but to the roles that are ascribed to them. The process of inequality starts early in life and receives continual reinforcement over lifetime. For instance, in the current generations of older adults, women were less engaged with technology (e.g., in childhood and education) and acquired less computer experience during working life than men. This higher level of experience and proficiency is conducive to Internet use in the retirement phase, assuming that older adults can maintain these resources. Having gained less experience and skills with IT (mental resources), women have higher barriers towards adopting and using innovative IT in later life. However, a few studies suggest that women's Internet use is more likely driven by social and communicative motives (Coelho and Duarte 2016; Thayer and Ray 2006; Wagner et al. 2010). This higher motivation might compensate the barriers discussed above so that we expect no gender difference in the frequency of social online activities (which is opposite to informational and instrumental activities).

H1. *Gender is associated with online activity such that online activity will be more frequent in men than in women.*

The level of Internet use varies a lot across generations (Anderson and Perrin 2017; Magsamen-Conrad 2015). Although older adults represent the most rapidly growing group of Internet users, frequency of their Internet use is still lower than in younger adults. Such differences are also present in older adults, for instance between young-older adults (age 65-74) and old-older adults (age 75+) (Anderson and Perrin 2017). In digital divide research, age is an important categorical inequality, which distinguishes young and old. Unequal distribution of two resources emerges. First is motivation to engage with technological innovations (mental resources). Innovation diffusion theory posits age-dependency on diffusion processes, with younger people making up the majority of early adopters while older adults are lagging behind (Gilly and Zeithami 1985). Because older adults did not experience today's ubiquitous presence of Internet in childhood and education, they perceive higher barriers to adopt and use Internet-based innovations. Second is the social network assisting in Internet use (social resources). With increasing age, older adults often experience diminishing social networks, e.g., loss of partner and reduced contact with children. Thus, they may have less support from family and friends, and depend more on help by others, which might not be available.

H2. *Age is negatively associated with online activity.*

Prior studies identify the educational background of older adults as an important predictor of Internet use (Chopik et al. 2017; König et al. 2018). The theoretical argument is that educational attainments in early life impact one's material and mental resources in later life. Thus, education is a categorical inequality, which describes the position of individuals and their relationships through positions between low and high. Higher formal education is usually associated with higher income, which then facilitates physical access. In other words, older adults with higher education have greater financial resources than those with lower level education to buy products and services for Internet use, e.g., computers, smartphones, equipment, broadband subscription, and paid content. Higher education may also increase older adults' mental resources for Internet use by allowing them to obtain professions and jobs that are more often characterized by frequent IT use. Gaining IT experiences during working life can prepare for Internet use after retirement through acquiring digital skills. A recent longitudinal study in Italy provides evidence for this lasting effect of school education on digital skills and Internet use of older adults (Kämpfen and Maurer 2018). On the other hand, less educated older adults more likely lack the material access and digital skills required, or perceive barriers towards Internet use, which then will undermine their use behavior.

H3. *Education is positively associated with online activity.*

In van Dijk`s theory, motivation is an important mental resource. For instance, motivation can materialize in the desire to be connected to the Internet and perform online activities that serve personal interests. This motivation can result from one's attitude towards consumer culture. The corresponding categorical inequality in digital divide research is cultural participation, defined as interest in cultural offerings such as movies, theaters, fashion, music events, and sports. Categorical inequalities exist between the curious and disinterested groups of people. The argument is that those who are curious about the outside world and open-minded towards societal developments accumulate higher motivation to engage in unknown domains than the disinterested. The Internet can be a useful tool to fulfill this curiosity. Indeed, prior studies suggest that older adults' cultural participation is associated with more frequent use of web and e-mail (Choi and DiNitto 2013; Gilleard and Higgs 2008; Näsi et al. 2012). Based on the motivational mechanism discussed above, we expect that higher cultural participation will lead to higher frequency of only those online activities that satisfy one's curiosity.

H4. *Cultural participation is positively associated with online activity.*

Next to the four socio-demographic characteristics, we hypothesize that perceived behavioral control is a positive predictor of older adults' Internet use (Chen and Chan 2014; Heart and Kalderon 2013). Perceived behavioral control (PBC) represents one's perception of internal and external constraints on behavior (Ajzen 1991; Taylor and Todd 1995). In UTAUT, PBC belongs to facilitating conditions, i.e., the degree to which an individual believes that an organizational and technical infrastructure supports their use of IT (Venkatesh et al. 2003). In our context, PBC includes older adults' beliefs in (1) their ability to use a device or service successfully, (2) having sufficient knowledge required for dealing with technology, and (3) receiving support from others in their technology adoption and use, in particular, from family and friends. Through the lens of van Dijk's theory, PBC can be regarded as a form of mental resource. Unlike the categorical inequalities considered above, PBC directly addresses the digital technology to be used; hence, it is a subjective summative evaluation of one's available resources for using this technology. Thus, higher levels of PBC will increase online activity.

H5. *PBC is positively associated with online activity.*

An important tenet of UTAUT is that socio-demographic characteristics can moderate the effects of psychometric factors such as PBC on behavioral intention and use behavior, respectively (Venkatesh et al. 2003). Moderation means that for a given categorical inequality, the effect of PBC will either be stronger or weaker for the dominating group compared to the subordinated group. First, prior research suggests that women tend to be more sensitive to their belief in mastering a new technology and therefore we assume PBC to be more important for women (Venkatesh et al. 2000). Second, because of decreasing cognitive and physical resources, old-older adults might give more attention to their mastery of digital skills and support by others (Hill et al. 2015); hence, we speculate that the effect increases with age. Third, older adults with higher education have learned to develop problem-solving strategies, which can assist them in overcoming barriers in using new technology (Diehl et al. 1995). These strategies are not bound to specific technologies but are of general nature. Therefore, the effect of PBC could be attenuated by high level of education for some online activities.

H6. *The association between PBC and online activity is stronger for women **(H6a)**, stronger for older individuals **(H6b)**, and stronger for less educated individuals **(H6c)**.*

3. Method

3.1 Data Collection and Participants

We conducted a questionnaire-based survey targeted at all older adults (age 65+) living in three districts in Mönchengladbach, a city of about 262,000 inhabitants (IT.NRW 2017). We chose the districts because they differed largely in population density (343; 2,400; 6,069 per square kilometer). Our research is integrated into a larger project, in which municipal stakeholders are taking part. Therefore, we received support from the local municipality in designing the study and collecting data. A municipal provider of geriatric care conducted a pretest to evaluate the questionnaire with respect to validity and comprehension. Based on the feedback obtained from nineteen participants, we made a few minor revisions (e.g., wording of questions and items). Additionally, we received support from the city administration, which provided us with the registered addresses. Further, the questionnaire was complemented by a cover letter signed by the respective district leader. The cover letter described the background of the project and invited citizens to participate.

In May 2017, the paper-based questionnaire was mailed to 6,170 older adults. Citizens were given six weeks to return the questionnaire (a stamped and addressed envelope was provided). They also had the option to fill in the questionnaire online by using an individual access code. Thirty-six participants chose this option. Considering that 100 addresses turned out to be invalid, the 1,302 responses received account for a response rate of 21.5%. This rate is comparable to prior surveys that also used posted self-administered questionnaires (Palonen et al. 2016).

The final sample includes users and non-users of the Internet (N = 1,222), defined by those who answered the question about online activities (scale: frequency ranging from never to daily). Because we use a convenient sample, we assessed whether the sample is representative of the population as a whole with respect to gender, age, and education. Specifically, we compared our sample with the population of older adults living in the city from which the sample was drawn (IT.NRW 2015). All differences in gender and age (based on 5-year intervals) are marginal. Our sample exhibits a greater share of participants holding a university degree (13.3% vs. 6.5%), while the share of participants with no high school education is smaller (1.2% vs. 6.1%).

3.2 Measurements

Answering the questions should impose low cognitive requirements on the participants; hence, we followed recommendations for designing questionnaires for older adults (Jobe and Mingay 1990; McColl et al. 2001). We took care that the questionnaire is barrier-free with respect to type and size of font, line spacing, layout, and coloring. We also avoided long and complex questions.

3.2.1 Predictors

Gender was defined as female or male. *Age* was calculated based on participant's year of birth. *Education* was measured by asking participants about their educational background. The question offered nine country-specific options (e.g., secondary education, vocational training, university degree). Based on the answers received, we derived three levels of education, i.e., "low" for primary and lower secondary education, "medium" for upper secondary education and vocational training, and "high" for academic education. This categorization considers definitions by the International Standard Classification of Education (ISCED) and peculiarities of the German education system.

Cultural participation was measured by participation in different cultural events. The rationale is that people who participate in a broader set of cultural activities exhibit greater interest in culture. We defined the question as follows: "How often do you leave the house for ..?" and administered a five-point frequency scale ("never," "few times," "several times per month," "several times per week," and "daily"). Five activities were listed: attendance of "music event," "theater," "museum," "cinema," and "restaurant, bar or coffee bar." Because we define cultural participation as the interest in culture, our variable should measure the breadth and variety of participation but not its intensity. Therefore, we count the number of activities that were attended (except "never"), thus cultural participation was measured on a scale ranging from 0 to 5 (Gilleard and Higgs 2008).

Perceived behavioral control was assessed by adopting three items from prior research (Ajzen 1991; Taylor and Todd 1995) and adjusting them to our study objective. We defined the items as follows: "I learn fast to deal with technology," "I don't have the knowledge to deal more intensively with technology" (item reversed), and "I know technology well." The five-point scale ranged from "strongly disagree" to "strongly agree." To ensure a common understanding of "technology", the question began with defining it as digital technology such as smartphone (cell-phone with Internet), tablet, and laptop/computer. Cronbach's alpha of our PBC instrument was 0.73, which suggests an acceptable level of internal consistency.

3.2.2 Online Activity

Our dependent variable was measured through frequency of six online activities. We chose activities reported in recent surveys as most prevalent in older adults (Anderson and Perrin 2017), including informational (searching the web, viewing pictures/videos), social (writing e-mails, writing comments/reviews), and instrumental activities (banking, shopping). We defined the question as follows: "How often do you use digital technology for ..?" and used a five-point frequency scale ("never," "few times," "several times per month," "several times per week," and "daily") .

3.3 Statistical Analyses

Our hypotheses testing relied upon ordinal regression analyses using IBM SPSS Statistics 25. First, we manually coded all received questionnaires and performed data cleaning prior to statistical analyses. Second, we conducted descriptive analyses (tables of frequencies, means, and standard deviations). Third, we assessed correlations for our independent and dependent variables. Then, we tested the assumptions of ordinal regression analysis including no multicollinearity and proportional odds. With respect to multicollinearity, we examined the Variance Inflation Factor (VIF) for each of the five independent variables. VIFs ranged between 1.13 and 1.26, thus they were below a standard cut-off of 2.5. This result suggests that multicollinearity did not affect our regression models. With respect to the proportional odds assumption, we used parallel lines tests, which reported non-significance for all regression models; hence, the proportional odds assumption was met. For each online activity, we defined a direct effects only model (which allowed us to test hypotheses H1-H5) and a model with interactions (which allowed us to test hypotheses H6a, H6b, and H6c.)

4. Results

4.1 Descriptive Statistics

Table 1 shows participant demographic characteristics. The sample was balanced in terms of gender. The largest age group was located between 65 and 74 years (total of 47.9%). On average, participants were 75.42 years old (*SD* = 7.10). Half of the participants had education at a medium level, while every seventh respondent reported education at a higher level. About one-third attended four or five different cultural activities (*M* = 3.10, *SD* = 1.67, on the 0-5 scale). Our sample exhibited considerable variance in perceived behavioral control (*M* = 2.86, *SD* = 1.08, on the 1-5 scale): While the lower end included 16.9% (PBC 1-2), the higher end comprised of 20.6% (PBC 4-5).

Table 1. Descriptive statistics for the five predictors

Variable	Scale	N	%	Variable	Scale	N	%
Gender	Female	608	50.2	Cultural participation	No activity	92	7.6
	Male	603	49.8		1 activity	301	24.8
Age	65-74	573	47.9		2 activities	218	18.0
	75-84	494	41.3		3 activities	180	14.8
	85-94	123	10.3		4 activities	182	15.0
	95+	7	0.6		5 activities	240	19.8
Education	Low	437	35.8	Perceived behavioral control (PBC)	1.0 ≤ PBC < 2.0	199	16.9
	Medium	612	50.1		2.0 ≤ PBC < 3.0	415	35.1
	High	173	14.2		3.0 ≤ PBC < 4.0	323	27.4
					4.0 ≤ PBC ≤ 5.0	244	20.6

Table 2 shows the descriptive statistics for online activities. When aggregating the answers for daily and several times per week, the three most frequent activities were searching the web (37.9 %), writing e-mails (26.9%), and viewing pictures/videos (20.7%).

Table 2. Descriptive statistics for online activities

Variable	N	Daily	Several times per week	Several times per month	Few times	Never
Informational online activities						
Searching the web	1,208	16.8%	21.1%	11.3%	9.2%	41.6%
Viewing pictures/videos	1,201	7.4%	13.3%	10.0%	22.6%	46.6%
Social online activities						
Writing e-mails	1,192	10.7%	16.2%	10.6%	15.0%	47.5%
Writing comments/reviews	1,202	0.7%	2.2%	2.8%	16.1%	78.1%
Instrumental online activities						
Banking	1,209	4.1%	7.4%	7.4%	4.1%	77.0%
Shopping	1,208	1.1%	1.5%	11.1%	22.4%	63.9%

Table 3 presents the correlation matrix. For all independent variables, correlations ranged from negligible to weak (highest coefficient of 0.29). Correlations between online activities were moderate to strong. A follow-up exploratory factor analysis identified one factor; however, note that we neither define types of online activities as psychometric constructs nor as reflective constructs. Between predictors and online activities, all correlations were significant and in the hypothesized direction.

Table 3. Correlations for predictors and online activities

Variable	1	2	3	4	5	6	7	8	9	10
1.) Gender										
2.) Age	0.06**									
3.) Education	-0.24**	-0.17**								
4.) Cultural participation	0.03	-0.29**	0.25**							
5.) PBC	-0.28**	-0.29**	0.27**	0.26**						
6.) Searching the web	-0.26**	-0.43**	0.34**	0.33**	0.60**					
7.) Viewing pictures/ videos	-0.22**	-0.38**	0.29**	0.30**	0.52**	0.80**				
8.) Writing e-mails	-0.19**	-0.40**	0.30**	0.40**	0.58**	0.79**	0.70**			
9.) Writing comments/ reviews	-0.14**	-0.28**	0.21**	0.22**	0.45**	0.53**	0.56**	0.55**		
10.) Banking	-0.23**	-0.23**	0.23**	0.19**	0.42**	0.49**	0.44**	0.48**	0.42**	
11.) Shopping	-0.20**	-0.33**	0.26**	0.29**	0.52**	0.66**	0.60**	0.65**	0.54**	0.62**

Note. Spearman's rank correlations. Ns range from 1158 to 1211. Gender: 0 = male, 1 = female. Education: 1 = low, 2 = medium, 3 = high. PBC = perceived behavioral control. * $p < 0.05$, ** $p < 0.01$.

4.2 Hypotheses Testing

Tables 4 to 6 present the results of our regression analyses, grouped into informational, social, and instrumental online activities. The tables show whether and how gender, age, education, cultural participation, and PBC were associated with online activities. Each table includes the direct effects only model (signified by column heading D) and the model with interactions (signified by column heading D+I) for each online activity. Associations are represented by odds ratios (OR), which state how the probability of achieving higher frequency of online activities changes for one-unit increase in the independent variable (*OR* > 1 for positive changes, *OR* < 1 for negative changes). For instance, age affects searching the web such that each one-year increase reduces the probability of higher frequency by 9% (*OR* = 0.91). In case of education, medium levels increase the probability of higher frequency of searching the web by 46% (*OR* = 1.46) compared to the reference group (low level of education). Explained variance ranged between 26% and 49% (R2).

Table 4. Ordinal regression analyses for informational online activities

		Searching the web				Viewing pictures/videos			
		D		D + I		D		D + I	
		OR	*p*	*OR*	*p*	*OR*	*p*	*OR*	*p*
Gender (=female)		0.69	0.003**	0.38	0.016*	0.71	0.007**	0.34	0.007**
Age		0.91	<0.001**	0.88	<0.001**	0.93	<0.001**	0.89	<0.001**
Education (reference: low)	High	4.34	<0.001**	25.78	<0.001**	2.17	<0.001**	15.55	<0.001**
	Medium	1.46	0.005**	2.97	0.018*	1.50	0.003**	2.55	0.040*
Cultural participation (reference: 0)	5	2.12	0.008**	1.98	0.018*	3.05	<0.001**	2.88	0.001**
	4	2.80	<0.001**	2.73	0.001**	3.11	<0.001**	3.13	<0.001**
	3	1.46	0.201	1.44	0.231	2.38	0.006**	2.38	0.007**
	2	1.70	0.072	1.67	0.091	2.22	0.011*	2.23	0.012*
	1	1.32	0.342	1.33	0.341	1.96	0.030*	2.03	0.026*
PBC		2.72	<0.001**	1.70	0.463	2.22	<0.001**	0.79	0.734
PBC × Gender				1.22	0.128			1.28	0.052
PBC × Age				1.01	0.370			1.02	0.096
PBC × Education High				0.57	0.004**			0.56	0.001**
PBC × Education Medium				0.78	0.104			0.83	0.200
N		1140				1131			
R2		0.48		0.49		0.36		0.37	

Note. D = direct effects. D + I = direct and interaction effects. OR = odds ratio. PBC = perceived behavioral control. R2 = pseudo r-squared (Nagelkerke's). * p < 0.05, ** p < 0.01.

Table 5. Ordinal regression analyses for social online activities

		Writing e-mails				Writing comments/reviews			
		D		D + I		D		D + I	
		OR	*p*	*OR*	*p*	*OR*	*p*	*OR*	*p*
Gender (=female)		0.87	0.270	0.63	0.267	0.98	0.895	0.54	0.328
Age		0.92	<0.001**	0.89	<0.001**	0.93	<0.001**	0.86	0.004**
Education (reference: low)	High	2.96	<0.001**	5.90	0.006**	1.74	0.020*	9.33	0.010**
	Medium	1.15	0.318	1.76	0.237	1.00	0.996	0.92	0.908
Cultural participation (reference: 0)	5	5.26	<0.001**	5.07	<0.001**	3.72	0.018*	3.62	0.022*
	4	4.95	<0.001**	4.84	<0.001**	4.15	0.012*	4.29	0.011*
	3	3.26	<0.001**	3.20	0.001**	3.64	0.025*	3.63	0.026*
	2	2.81	0.002**	2.77	0.003**	3.52	0.029*	3.56	0.029*
	1	1.74	0.103	1.74	0.106	2.77	0.079	2.85	0.074
PBC		2.70	<0.001**	1.29	0.732	2.70	<0.001**	0.62	0.643
PBC × Gender				1.11	0.418			1.19	0.338
PBC × Age				1.01	0.258			1.02	0.133
PBC × Education High				0.81	0.270			0.64	0.059
PBC × Education Medium				0.87	0.347			1.01	0.947
N		1125				1133			
R2		0.46		0.47		0.31		0.32	

Note. D = direct effects. D + I = direct and interaction effects. OR = odds ratio. PBC = perceived behavioral control. R2 = pseudo r-squared (Nagelkerke's). * p < 0.05, ** p < 0.01.

Table 6. Ordinal regression analyses for instrumental online activities

		Banking				Shopping			
		D		D + I		D		D + I	
		OR	*p*	*OR*	*p*	*OR*	*p*	*OR*	*p*
Gender (=female)		0.54	<0.001**	0.66	0.468	0.74	0.033*	0.80	0.129
Age		0.95	<0.001**	0.95	0.244	0.93	<0.001**	0.95	0.146
Education (reference: low)	High	2.10	0.001**	2.58	0.243	2.07	<0.001**	4.80	0.038*
	Medium	1.09	0.650	0.90	0.874	1.22	0.218	3.84	0.018*
Cultural participation (reference: 0)	5	1.42	0.362	1.45	0.337	2.96	0.004**	2.93	0.004**
	4	1.21	0.639	1.24	0.587	3.06	0.003**	3.01	0.004**
	3	1.31	0.514	1.33	0.490	2.85	0.007**	2.81	0.008**
	2	1.50	0.323	1.53	0.300	2.10	0.061	2.10	0.061
	1	1.03	0.942	1.04	0.921	1.50	0.310	1.50	0.306
PBC		2.24	<0.001**	2.28	0.357	2.77	<0.001**	5.95	0.031*
PBC × Gender				0.94	0.706			0.80	0.129
PBC × Age				1.00	0.987			0.99	0.606
PBC × Education High				0.95	0.805			0.76	0.197
PBC × Education Medium				1.06	0.774			0.69	0.033*
N		1138				1138			
R2		0.26		0.26		0.39		0.39	

Note. D = direct effects. D + I = direct and interaction effects. OR = odds ratio. PBC = perceived behavioral control. R2 = pseudo r-squared (Nagelkerke's). * p < 0.05, ** p < 0.01.

As the tables indicate, women were less likely to search the web (*OR* = 0.69, *p* = 0.003), to view pictures/videos (*OR* = 0.71, *p* = 0.007), to use online banking (*OR* = 0.54, *p* < 0.001), and to shop online (*OR* = 0.74, *p* = 0.033) but gender had no effect on frequency of writing emails and writing comments/reviews. Age had a negative effect on all online activities, with odds ratios between 0.91 and 0.95 (*p* < 0.001). High levels of education increased the probability of usage for each online activity (OR ranging from 1.74 to 4.34). However, medium levels of education led to higher probability only for searching the web and viewing pictures/videos (*OR* = 1.46 and *OR* = 1.50, respectively). Cultural participation was positively associated with all but one online activity (banking), and dependent on the number of cultural activities attended. PBC had a direct effect on each online activity, while the six odds ratios exhibited rather low variance (in the interval between 2.22 and 2.77).

We analyzed whether gender, age, and education moderated the effect of PBC (models provided in the D+I columns). Our results show that high levels of education reduced the effect of PBC for searching the web and viewing pictures/videos. In case of shopping, medium levels of education lowered the effect of PBC.

To further explore the nature of the interaction effects, we conducted a follow-up analysis, in which we split the sample based on education as the only significant moderator variable. We then repeated the regression analysis (direct effects) for each subsample. Education has three levels, thus we retrieved odds ratios of PBC differentiated for the low, medium, and high levels. With respect to searching the web, OR decreased with higher education, i.e., 3.72 for low, 2.57 for medium, and 2.05 for high. This decrease also held true for viewing pictures/videos with 2.78 for low, 2.19 for medium, and 1.66 for high. In case of online shopping, PBC had the weakest effect for participants with medium levels of education (*OR* = 2.44), whereas the effect was strongest for the participants with high levels (*OR* = 3.49).

Table 7 provides a summary of our hypotheses testing. Hypothesis H1 about gender was supported for informational and instrumental activities but not for social activities. The hypotheses about direct effects of age (H2-), education (H3+), and PBC (H5+) received full support. Cultural participation explained all online activities except online banking, which supports H4. Our results showed no moderation of PBC by gender and age, which is contrary to hypothesis H6a and H6b, respectively. High education increased the effect of PBC compared to low education in case of informational activities, which lends support for hypothesis H6c.

Table 7. Summary of hypotheses testing

Hypothesis	**Online activities**		
	Informational	**Social**	**Instrumental**
H1: Gender	Supported	Rejected	Supported
H2: Age	Supported	Supported	Supported
H3: Education	Supported	Supported	Supported
H4: Cultural participation	Supported	Supported	Supported for shopping
H5: PBC	Supported	Supported	Supported
H6a: PBC × Gender	Rejected	Rejected	Rejected
H6b: PBC × Age	Rejected	Rejected	Rejected
H6c: PBC × Education	Supported	Rejected	Supported for shopping

Note. PBC = perceived behavioral control.

5. Discussion

5.1 Findings

Our research set out to analyze the factors explaining differentiated online activities in older adults using primary survey data collected in Germany. We examined three types of online activities, namely, informational, social and instrumental. Overall, our study results suggest that the role of some predictors is contingent upon the online activity.

With respect to the two informational online activities, we find that their frequency was predicted by all the factors studied. We observe that the odds for highly educated adults were twice as high for searching the web than for viewing pictures/videos. This stronger effect can be explained by findings from cognitive research showing that actively searching the web requires more resources than consuming multimedia content (Litt 2013). Further, we observe that those with higher cultural participation were more likely to search the web and to view pictures/videos. We construe this relationship that one's curiosity and interest in consumer culture can be satisfied by using search engines and multimedia platforms that allow access to culture content. Participation in one or more cultural activities predicted viewing pictures/videos, whereas this effect started at four or more cultural activities for searching the web. This difference could be due to web search being a more focused activity requiring a deeper interest in culture. For instance, users need to formulate explicit search queries by themselves, and validate search results in an iterative process leading to the final success.

Older adults will activate these resources depending on their interest in consumer culture; hence, the frequency of searching the web will increase at a higher level of cultural participation compared to viewing pictures/videos.

For the two social online activities, we find the pattern that age, education, cultural participation, and PBC were predictors, while gender was not. Social online activity was the only type for which gender was not a predictor. This finding corroborates our expectation that women's higher motivation towards social use can outweigh lower experience and lack of digital skills (Scheerder et al. 2017). Further, the effect of higher education was considerably stronger for writing emails than for writing comments/reviews. An explanation could be that individuals with higher education tend to prefer communication channels that allow personal, complex and structured messages. Note that writing comments/reviews on the Internet is different from writing emails, because comments/reviews are most often non-personnel, anonymous and writing may require less mental resources.

Considering the two instrumental online activities, men and those who were younger, with higher education, and reported higher PBC had greater odds for online banking and shopping. However, cultural participation only enhanced the frequency of shopping but not banking. Specifically, participation in three or more cultural activities predicted shopping online, while there was no effect at all for banking. This difference suggests that online shopping can be a tool for older adults to satisfy their curiosity. Note that banking is a necessary activity for all individuals, irrespective of their interest in consumer culture.

Our digital divide model integrates PBC, which was a positive predictor for all six online activities and its direct effect was rather similar (as signified by the small range of odds ratios). It is worth noting that the effect was neither moderated by gender nor age. Based on the mechanism described in our hypotheses development, it is likely that women's trust in PBC did not differ from men. Similarly, the assumed age-related decrease of cognitive and physical resources did not lead to more sensitivity to believe in PBC. However, we find that education moderated PBC for the two informational online activities, i.e., high education attenuated the effect. This finding could be explained by motivational differences, such that those with high education more likely regard the Internet as a useful tool for knowledge acquisition. This specific motivation could counterbalance lower levels of PBC, which is possible because motivation and PBC are both mental resources. We acknowledge that only a limited number of prior studies in the older adults context tested moderators (Choudrie et al. 2018; Lian and Yen 2014). This limitation of the empirical knowledge also holds true for UTAUT, as articulated by Venkatesh et al. (2016) in a comprehensive review of UTAUT-based studies.

In summary, we believe that our empirical findings contribute to the literature by providing a better understanding of differentiated online activities in older adults. Our approach enabled us to uncover important differences in the roles of gender, cultural participation and PBC as predictors.

5.2 Implications

Our study results have the following implications for research. First, as the range and scope of online services is increasing, opportunities exist to test the validity of our propositions for further online activities. Our research provides the foundation for deeper inquiry as signified by the high explanatory power for six online activities that vary considerably. Of particular interest are social networks and messaging services (e.g., Facebook, Twitter, WhatsApp), and health-related online services, which attain increasing importance for this target group. Second, based on our model, fellow researchers can examine the usefulness of further categorical inequalities such as ethnicity and household (van Dijk 2005; van Dijk 2006). Ethnicity is a *personal* categorical inequality, which differentiates majority and minority. Household as a *positional* category assigns individuals to single or family. Third, because we find education as a moderator of perceived behavioral control in case of informational online activities, future research can now focus on educational subgroups (Hargittai et al. 2018). For instance, studies could differentiate further levels of formal education, and in particular, consider experiences obtained during working life.

Our research also has important practical implications. Our results help identify subgroups requiring training, assistance or tailored online services. This identification is possible because of the categorical inequalities underlying our digital divide model. Moreover, subgroups can be derived from combining two or more subordinated groups. The largest subgroup comprises older women with low education and lack of cultural participation. Their risk of exclusion from the digital world will be amplified if their belief in mastering the Internet (PBC) is rather low; this risk is even more critical, because they cannot compensate PBC with high education. First, training should target the advancement of digital skills. Informational, social, and instrumental activities require different skill sets. Some online activities demand more mental resources (e.g., for information processing and decision-making), e.g., searching the web and online banking, because the user takes a much more active role. Training of particular skills, such as retrieving and evaluating rich information, will also enhance PBC, which is key for all online activities. Second, the enhanced understanding of older adults' online activities can support policy-makers and other societal stakeholders in devising legislation and interventions targeted at older adults. For instance, legislation should guarantee fair use of a broad set of different online services for all groups defined by categorical inequalities. Third, implications arise for online service providers to tailor their services to the requirements of the groups discussed above. For instance, recent advancements in Internet-based applications allow implementing responsive user interfaces aligned with individual needs, ranging from devices and network quality to diverse user preferences.

5.3 Limitations

The results of this study should be interpreted in light of its limitations. The first limitation is the cross-sectional nature of the study, which does not allow us making causal inferences. Older adults' use of the Internet is a process that evolves over time. Cross-sectional data only provides a snapshot of that process. Longitudinal studies are required to validate our propositions. The second limitation of the study is its focus on six online activities, which naturally cannot reflect the full diversity of older adults' online activities. Our selection was motivated by spanning a wide array including informational, social, and instrumental online activities. In addition, our measurement of online activities relied upon self-reported frequencies measured on an ordinal scale. Thus, our data is subjective and approximate. Asking the participants to recall the time spent for such activities could yield continuous data of higher precision. However, this approach was not feasible for our target group of older adults, since they might not be able to recall their time spent. Self-reports were also used in the few studies investigating specific online activities, either by engagement, i.e., yes/no (Choi and DiNitto 2013; Gell et al. 2013; Hong and Cho 2017), or scaled frequency, e.g., five-point scale as in our study (Nimrod 2018; van Deursen and Helsper 2015). Third, our moderation analysis did not include experience for which UTAUT posits an increasing effect of PBC (Venkatesh et al. 2003). Fourth, our survey targeted older adults living in an urban area in Western Europe; hence, our results may not necessarily be generalized to older adults living in rural areas or other regions.

6. Conclusion

Understanding older adults' Internet use is important for the design of online services, training programs and policies targeted for the elderly. Although Internet use is changing tremendously and the range of online activities is broadening, the literature is insufficient in informing us about the factors explaining specific online activities. Our study contributes a nuanced understanding of older adults' Internet use by examining four socio-demographic characteristics (i.e., gender, age, education, and cultural participation) and perceived behavioral control in predicting informational, social, and instrumental online activities. Our results shed light on the important differences of gender and cultural participation (direct effect) and education as a moderator of PBC in case of informational online activities. The findings have implications for providers to tailor their online services to the needs of older adults as a growing consumer group, and informs policy-makers and societal stakeholders in designing programs and interventions targeted at older adults.

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