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How old are you really? Cognitive age in technology acceptance

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ABSTRACT

With increasing trends toward global aging and accompanying tendencies of (older) individuals to feel younger than they actually are, an important research question to ask is whether factors influencing IT acceptance are the same across individuals who perceive themselves to be as old as they actually are (i.e., cognitive age = chronological age) and those that perceive themselves to be younger than they actually are (i.e., cognitive age < chronological age). We conduct an empirical analysis comparing these two groups in the context of mobile data services (MDS). Our results show that for the "young at heart," perceived usefulness, perceived ease of use and perceived enjoyment play significant roles in their IT acceptance decisions, whereas for those who perceive themselves to be as old as they actually are, perceived ease of use and subjective norms were significant. Practical implications regarding use of cognitive age as a basis for customer segmentation in IT industries as well as theoretical implications about meaningful age in human computer interaction research are offered and discussed.

1. Introduction

Age differences have been known to play an important role in understanding human perceptions and behavior in various research domains including psychology [43,49], organizational behavior [e.g.,22,55], and marketing [e.g.,14,64]. The role of age is equally or more important for information systems (IS) research since the actual behavior [40] as well as attitude [16] with regard to technology adoption is critically linked to a user's age. Also, due to the fast-paced development and introduction of new technologies, different age generations are inevitably confronted with different generations of technologies. For example, most adolescents today grew up with the graphical user interface (GUI) and have never used command line interfaces (CLI); e-mail is the communication medium of choice for today's managers whereas those newly entering the workforce prefer to interact with one another via interactive social media such as Facebook or Twitter [38]. As computer pioneer Alan Kay so aptly put it, "[T]echnology is anything that was invented after you were born." Hence, attitudes toward technology may vary largely depending on one's age.

However, despite its significance in technology adoption and use, age has received little attention in IS research [59]. In the IS literature, age has typically been treated as a demographic control variable and measured as the number of years from birth (i.e., chronological age) without much consideration regarding the functional meaning of age in the individuals' minds. Chronological age measures the actual number of years that a person has lived and therefore does not reflect the idiosyncratic meaning of this number to different individuals. For example, age 40 may be perceived as old by some but young by others depending on their life satisfaction, activity level, health and culture [13]. Nonetheless, chronological age provides an objective measure of life length of each individual and has been widely used in the IS literature. For example, in testing the invariance of the factors driving technology adoption across different age groups Lai and Li [33] divided the subjects into young and old based on chronological age. Such routine and mechanistic operationalization of age may be problematic as the population ages and information technologies become more pervasive and an integral part of many everyday products and services [63], with the separation between work and personal use of such systems becoming blurred [28]. Mobile technologies such as smartphones in particular, serve as both personal consumer information appliance, as well as work platform. In short, discretionary adoption decisions regarding mobile technologies for personal use may also impact work performance. This casts the IT adoption decision as increasingly one of consumer choice, where the variance in age perception within the same demographic age group has received increasing attention. Research in psychology and marketing has questioned the appropriateness of using simple chronological measures of age for making inferences or predictions about attitudes or behaviors [e.g., 4,44,50,51]. As Schiffman and Sherman [50, p. 188] state, "[A]ge is revealing itself to be more a state of mind than a physical state." Indeed, it is self-perception of one's own age rather than chronological age that influences one's values and

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behaviors, as well as attitudes towards technology. For example, in a study of American elderly consumers, seniors who perceived themselves to be younger than their chronological age reported heavier use of the Internet than those whose self-perceived age was older [18]. The inadequacy of using chronological age stems from the fact that individuals' perceptions, attitudes and behaviors are influenced to a greater extent by how old a person feels (i.e., cognitive age) than by how long she has lived (i.e., chronological age) and that people often perceive themselves to be at an age different from their chronological age [4].

While other disciplines such as psychology, marketing, and organizational behavior have begun to employ self-perceived age as the measurement of choice [e.g., 52,54], IS research has used age measures based solely on birth-date (i.e., chronological age) [e.g., 10]. The frequent and unchallenged use of chronological age in IS research is understandable as it exhibits several characteristics that make it an attractive research measure. Chronological age is quantitative, unambiguous, can often be coded in continuous form and is relatively easy to acquire and validate. However, despite these desirable characteristics, the use of chronological age may limit our understanding of the role of users' age in technology acceptance and use – either as a focal attribute of interest determining technology adoption attitudes and perceptions or as a control or moderator variable that affects other variable relationships [e.g., 11,28–30,35,40,41,59,65]. Chronological age may be especially limiting as there may be an increasingly wide range of variation in perception of age amongst people in the same chronological age group. The variance of age perception is reported to be even more pronounced within the elderly age group. The baby boomers (born between 1946 and 1964) in the U.S. in particular have been found to be more active and in touch with advances in technology than would be dictated by general predictions based on their chronological age [17,48].

Our research addresses the question of whether and how self-perceived age affects technology adoption and usage behavior: does self-perceived age reveal heterogeneity among chronologically homogenous user groups? In other words, how do differences in self-perceived age of same-aged individuals influence user perceptions and behavior? What aspects of users' technology adoption/acceptance behavior would be affected? Such questions are particularly important with the increasing use of IT-enabled products and services in the mass market such as mobile data services, hand-held computational devices, smartphones, and game consoles that target end users exhibiting greater age variance relative to information systems users within organizational settings. If there are significant differences among same-aged users of varying cognitive age, conventional user segmentation approaches based solely on chronological age may produce limited (and perhaps misleading) insight into users' needs and factors affecting technology adoption.

The main objective of this paper is to critically revisit the use of age in technology adoption research. This paper investigates whether the theoretical relationships in models of technology acceptance vary depending on one's age perception. More specifically, we focus on discrepancies in age perceptions – i.e., differences between birth-date-based chronological age and cognitive age. We believe that our current focus on age is important and timely for the following reasons. It is generally accepted that the global population is aging, at least for most industrially developed countries [57]. As the population ages, discrepancies in age perceptions have also begun to widen. Since the 1950s, research has consistently reported patterns of discrepancies between one's chronological age and cognitive age, and such discrepancies increase with the increase in chronological age [3–6,8,47]. Furthermore, research findings indicate that such discrepancies have potentially significant implications in business [e.g., 5,62], as well as in technology-related attitudes and behaviors [18]. Therefore, we contend that as the age of information technology users increases, we will witness a widening of discrepancies in age perceptions among users, with simple chronological age becoming a less reliable predictor of technology attitudes and adoption [36]. Moreover, as information technology constitutes an integral part of our daily life, the age range of the information technology users is becoming wider than ever (e.g., mobile phone), and it has become imperative to better understand the complex nature of the impact of age on information technology usage and adoption decision patterns in both personal and work use contexts. In short, societal changes and technology trends have rendered age as an important construct in its own right, rather than a secondary variable in explaining important IS phenomena such as technology adoption decision making. Hence, this calls for a more nuanced consideration of age than has been used when age was considered secondary in importance.

The current paper is organized as follows. We first present a review of age measures in prior IS research. The ensuing section presents prior theoretical treatments of cognitive age and individual users' technology acceptance/adoption. Our research model and hypotheses are discussed in the next section, followed by our research methods and results. We conclude with a discussion of our major findings and implications for future research and practice.

2. Use of age in IS research: An assessment of the literature

We first conducted a review of the IS literature to ascertain how widely measures of age were used in prior IS research. To do so, we reviewed over a decade of IS research published in the leading MIS journals – *MIS Quarterly*, *Information Systems Research* and *Journal of Management Information Systems*.

More specifically, we identified all empirical research papers employing primary data collection (i.e., research using surveys, interviews, experiments or a combination of these) that deal with individual-level phenomena (e.g., technology acceptance, IS use, user satisfaction, IT professionals) published in the aforementioned journals between January 1996 and June 2009 – 365 articles from *MIS Quarterly*, 307 articles from *Information Systems Research* and 459 articles from *Journal of Management Information Systems*. From a total of 1131 articles published in these journals, 256 (22.37%) fit our criteria for inclusion in our review. Table 1 summarizes our sample of articles for our literature review by journal and by empirical research approach.

Next, in order to ascertain how the age construct was used in IS research, we categorized each article by noting whether and how age was used in the paper – 1) research participants' (i.e., survey respondents, experimental subjects, or interview informants) age may have been measured and used as an independent variable in the empirical analysis; 2) participants' age may have been measured and used as a moderator variable; 3) age may have been measured and used as a control variable; 4) age may have been collected but not used in the analysis but used to report the participant characteristics (i.e., demographics); and finally 5) age may not have been reported at all. Table 2 summarizes the classification.

Several important observations are obtained from our review of the literature. First and foremost, we note that age is a pervasive measure in IS research. Even if participants' age is not used directly in the empirical analysis as an independent, moderator or control variable, it is usually collected and reported – participants' age was reported in 58.5% of the articles (148 of 253). Second, the review of the literature suggests that despite the significance of the role of age in individual-level IT related phenomena, age has indeed received little attention from IS researchers [59] – participants' age was used as a main modeling construct (i.e., as an independent or moderator variable) in only 3.9% of the articles (10 of

Table 1
Individual-level IS research (1996–2009).

	MISQ	*ISR*	*JMIS*	Total
Survey	42	36	60	138
Experiment	25	37	46	108
Mixed method	0	3	4	7
Total	67	76	110	253

Notes: Mixed method refers to articles that use a combination of empirical approaches – e.g., interview + survey, survey + experiment, and case study + survey.

Table 2
Use of *Age* in IS research.

	MISQ	*ISR*	*JMIS*	Total
Independent variable	0	3	3	6
Moderator variable	4	0	0	4
Control variable	22	25	22	69
Participant characteristics	17	22	30	69
Not reported	24	26	55	105
Total	67	76	110	253

253). In many cases (27.3% of articles), age was used only in a secondary role as a control variable. Finally, while not explicitly shown in our analyses, it is worth noting that in *all* cases where age was measured and used or at least reported, the birth-date-based chronological age was used.

In summary, age has not been a focal research variable in IS research to date. It is perhaps for this reason that much of IS research has used the chronological age measure. Because of contextual difference such as the age composition and the characteristics of the technologies examined at the time of these studies, the loss of information regarding differences in individual perception of age was acceptable in lieu of the more parsimonious research model that resulted. However, as discussed in the previous section, variance of perceived age within the same chronological age group has recently emerged as an important social phenomenon with the aging population. Using chronological age in explaining many IS phenomena will not be able to explain variations that exist among people within the same chronological age group. Cognitive age may help understand variances in IT-related phenomena that remain unexplained when relying on chronological age measures. Ample evidence exists from psychology, gerontology, education and consumer behavior regarding the problems of assuming the same characteristics and attitudes of same-aged individuals [4,44,50,51]. For example, contrary to popular rhetoric, it is unclear whether the millennial generation (also referred to as the net generation, or "digital natives") born after 1980, is actually homogeneous with respect to their technology attitudes and usage behaviors [37], nor whether they exhibit uniformly greater use of technologies in the workplace relative to Generation X individuals (i.e., those born between 1965 and 1980) [61]. IS research is thus also urged to incorporate the concept of cognitive age in its rhetoric to take into account individual differences in cognitive age beyond what was explained by chronological age. Therefore, clearly, there is a need to better integrate age into our theoretical models in the field of IS.

3. Theoretical background and research model

3.1. Cognitive age

Cognitive age has been validated and used in aging research [e.g., 7,44] as well as in consumer research [e.g., 56,62]. Cognitive age is comprised of four dimensions of age perception: (1) how old an individual feels, (2) how old an individual looks; (3) how an individual does things favored by members of a certain age group; (4) how similar an individual's interests are to members of a certain age group [4,32]. Evidence from aging research suggests that most adults who have reached their middle-age tend to feel younger than they actually are and such tendencies become more pronounced as people get older [32]. Furthermore, consumer research has found that cognitive age influences consumption orientation and purchasing behaviors [23,51]. As IT products and services are increasingly being targeted to consumers, who exhibit great heterogeneity in attitudes and behaviors, it is important to understand the impact of (older) people's self-perceptions with regard to aging [62]. Moreover, there is an increasing trend towards ubiquitous information systems and the consumerization of enterprise IT, as privately-owned IT devices (e.g., smartphones, tablets, laptops) and public network services (e.g., wireless) become an integral part of the organizational IT infrastructure [42,45,60]. Thus, understanding how attitudes and behaviors related to IT are influenced by differences in cognitive rather than chronological age is important not just for consumer-oriented IT research, but also for understanding organizational IT users' attitudes and usage of multipurpose information technologies and ubiquitous information services.

Even if individuals are of the same (chronological) age, they may attribute very different meaning to what their age means for them [5]. There are three commonly used concepts of self-perceived age: 1) how old an individual feels, looks and acts, commonly referred to as cognitive age [3,4]; 2) with which age cohort an individual identifies herself, referred to as social or comparative age [34]; and finally 3) how old the individual desires to be – ideal or desired age [5].

These alternative measurements of self-perceived age enable a better understanding of the discrepancies and their relationship to individuals' attitudes and behaviors. Among these self-perceived age concepts, cognitive age has been primarily studied in consumer research. More specifically, cognitive age has been found to influence consumption orientation and purchase behaviors [3,23–25,31,51]. In this study, we focus on the cognitive age concept of self-perceived age, as the domain of interest (i.e., technology acceptance) relates mostly with consumption orientation and behaviors.

3.2. Age and technology acceptance

Our review of prior IS research in Section 2 indicates that age has received limited attention in IS research. Among the large number of technology adoption research studies, we found only three key articles that focus specifically on the effects of age on technology adoption and use [40,41,59]. We first review each of these papers in detail to gain an appreciation of how age impacts technology acceptance and use.

Morris and Venkatesh [40] studied the influence of age on technology adoption in an organizational setting. They found that perceived ease of use and subjective norm have a more salient influence on initial technology adoption decision for older workers than younger workers. However, this contrasting effect was found to diminish over time as workers gained more experience using the system.

In Morris et al. [41], age was found to have a significant moderating impact on key relationships in the theory of planned behavior (TPB). With increasing age, a greater emphasis on attitude toward using the technology was placed in decisions regarding technology adoption. Interestingly, this effect varied depending on gender, with the effect stronger for men compared to women. In contrast, the impact of subjective norm on technology acceptance was found to be stronger with increasing age. However, this effect was only found for the female user population but not for males.

In an extensive study striving to develop a unified theory of technology acceptance and use, Venkatesh et al. [59] investigated the moderating impact of age on the key theoretical relationships of technology acceptance. More specifically, they found the effect of performance expectancy on behavioral intention to use to be stronger for younger workers; whereas the effect of effort expectancy and social influence on behavioral intention to use and that of facilitating conditions on actual usage were found to be stronger for older workers.

In summary, it is evident that age does affect user attitudes and behaviors related to technology acceptance and use. However, it is also interesting to reiterate that birth-date-based chronological age was consistently used as the measurement. Given the general population trends toward global aging and the increases in discrepancies between self-perceived age and chronological age, it is worth investigating whether similar impacts persist for people whose self-perceived age is different from their chronological age. We report on findings from our empirical study examining this issue in the subsequent sections.

4. Research model and hypotheses

Technology acceptance has a rich body of literature and there seems to be general consensus with respect to the factors that influence an individual's technology acceptance decision [59]. Although different terminology may be used, these factors include some form of performance expectancy (e.g., perceived usefulness), effort expectancy (e.g., perceived ease of use), social influence (e.g., subjective norm), and facilitating conditions. Depending on the target technology of focus and other situational factors of relevance (e.g., voluntary vs. mandatory use contexts) the relative importance of these factors in determining technology adoption varies, with additional factors required in certain unique contexts.

In the present study, the target technology of focus is mobile data services (MDS). Mobile data services are representative of the multipurpose information appliances that are representative of the trend towards ubiquitous information systems and the consumerization of enterprise IT discussed in earlier sections. Such systems may be viewed as being both utilitarian and hedonic in use purpose, as well as representative of consumer-oriented IT adoption decisions that may be more prone to influence from differences in perceived age. Simultaneously, as the boundaries between work and personal life blur, such consumer-oriented IT adoption will have important implications for understanding organizational IT adoption and use, in particular as ubiquitous information systems access becomes important for knowledge workers [60]. Hence, MDS adoption is an appropriate context within which to examine our research question. Our data collection efforts were targeted toward current users of MDS, thus the dependent variable of interest was behavioral intention to continue to use MDS. Furthermore, data was collected in Hong Kong, due to its world-class infrastructure for mobile IT applications and its position as a leader in mobile IT diffusion. According to the International Telecommunication Union (ITU) Information Society Statistics Database Hong Kong ranked fourth in 2005 in terms of mobile penetration worldwide and fifth in mobile broadband penetration, owing in part to it providing the least expensive cost of access – measured as a proportion of monthly income. It was also ranked in the top 10 in active mobile broadband subscriptions per 100 inhabitants. This makes Hong Kong SAR the appropriate context within which to examine intentions to use MDS. Since MDS is a personal technology widely used for services that not only relate to work (i.e., utilitarian purposes) but also to personal enjoyment (i.e., hedonic purposes), we include perceived enjoyment as an important construct in the research model [58]. Also, since the mobile communications infrastructure in Hong Kong already provides excellent support, the influence of facilitating conditions on technology acceptance and use was deemed to be minimal. Consequently, we exclude this construct from our model. The overall research model used is presented in Fig. 1.

The focus of our research is whether cognitive age would impact the overall mechanism of technology acceptance among the aged population. In particular, we examine whether individuals who perceive

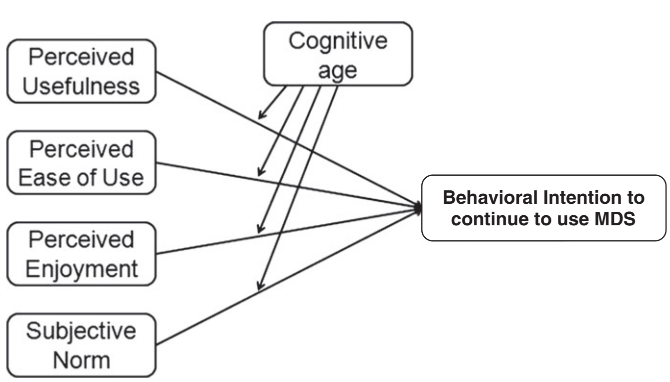

Fig. 1. Research model.

themselves to be younger than they actually are exhibit heterogeneity in the strengths of the theoretical relationships. We do not formulate explicit hypotheses regarding the cognitively older, as there has been relatively little prior research for the age groups within which cognitive age is greater than chronological age, namely adolescents. In other words, the comparison is between individuals of varying cognitive age; the necessary comparison for our purposes involves contrasting the "cognitively young" – those who perceive themselves to be younger than they are (i.e., cognitive age < chronological age) and those who perceive themselves to be as old as they actually are (i.e., cognitive age = chronological age). Consequently, we formulate our hypotheses as null hypotheses for each of the theoretical relationships in our research model:

H1$_0$ The influence of perceived usefulness on behavioral intention to continue to use MDS is the same for individuals whose cognitive age equals their chronological age and the cognitively young.

H2$_0$ The influence of perceived ease of use on behavioral intention to continue to use MDS is the same for individuals whose cognitive age equals their chronological age and the cognitively young.

H3$_0$ The influence of perceived enjoyment on behavioral intention to continue to use MDS is the same for individuals whose cognitive age equals their chronological age and the cognitively young.

H4$_0$ The influence of subjective norm on behavioral intention to continue to use MDS is the same for individuals whose cognitive age equals their chronological age and the cognitively young.

5. Research methodology

We adopted existing validated measures for our model constructs where possible. (See Appendix 1 for the scales used in this study.) The scales for perceived usefulness, perceived ease of use, perceived enjoyment and subjective norm were measured using extensively validated items from prior technology adoption research [58,59]. The instruments used in this research were adapted and reworded to suit the context of MDS. Chronological age was calculated in years based on the self-reported date of birth of survey respondents. Cognitive age was assessed using the age–decade scale [4,13,26]. Respondents were asked to select their cognitive age bracket scaled in intervals of 10 years (i.e., 20s, 30s, 40s, 50s, 60s, 70s, 80s, or 90s) in response to four questions of the form, "I feel like I'm in my ____," "I look like I'm in my ____," "My interests are those of a person in his/her ____," and "I do the things a person does in his/her ____." The four subscales are averaged to yield a cognitive-age score [4,13,26,53].

We conducted an online survey of MDS adoption in Hong Kong to collect the data for empirical analysis. Survey respondents were recruited using a banner advertisement made available on a non-profit public website run by the Hong Kong government – namely a government portal enabling electronic access to governmental services such as tax returns and visa applications. To encourage participation in the online survey, a number of prizes (e.g., mobile handsets, MP3 players) were offered based on a random draw. The online survey was accessible online for three weeks. We received 664 responses from both potential and current users using MDS mainly for communication purposes. Table 3 shows the demographic characteristics of the survey respondents.

The correspondence between chronological and cognitive age for the sample ($N = 664$) is shown in Table 4. In this study, we focus on the pre-Net generation, those who are (chronologically) at least in their 30s (gray and black shaded cells in Table 4). This was because it is commonly believed that people would feel younger than they actually are

Table 3
Sample characteristics.

	N	Percentage (%)
Gender		
Male	237	35.7
Female	427	64.3
*Annual income (HKD)**		
<$50,000	41	6.1
$50,000–$100,000	415	62.5
$100,000–$150,000	147	22.1
>$150,000	50	7.5
Education (highest level completed)		
Elementary school	26	3.9
Middle/high school	303	45.7
Professional training	57	8.6
Associate degree	9	1.4
Bachelor's degree	187	28.2
Master's degree	62	9.3
Professional degree	19	2.9
Doctoral degree	0	0.0
Age (chronological)		
13–19	47	7.1
20–29	338	50.9
30–39	193	69.2
40–49	74	26.5
50–59	12	4.3
Total	664	100.0 (%)

* The currency exchange rate is 1 USD = 7.76 HKD. The median monthly income of the working population in Hong Kong in 2006 was $10,000 (HKD), i.e., an annual income of $120,000 (HKD). (Source: Census and Statistics Department (2007). *Thematic Report: Household Income Distribution in Hong Kong*. Hong Kong: HKSAR Government.)

only after reaching a certain age (e.g., at least 30) [56]. Thus, we sampled respondents in the chronological age decade from 30s to 50s and divided the selected sample into two groups, by the chronological age decade and the cognitive age decade to investigate the moderating effect of cognitive age on the antecedents of technology adoption. The dataset was divided into two groups: (1) those who perceive themselves to be as old as what they actually are (i.e., chronological age = cognitive age); and (2) those who perceive themselves to be younger than they actually are (i.e., cognitive age < chronological age). The size of the final sample used in the analysis was $N = 266$. The selected sample for hypothesis testing has 266 valid responses (gray and black shaded cells in Table 4).

6. Data analysis and results

The research model was tested using partial least squares (PLS), a powerful second-generation multivariate technique for analyzing causal models that involve multiple constructs with multiple observed items [12]. All constructs were modeled as reflective measures. The significance of path coefficients was determined using 200 bootstrap samples of 200 randomly selected observations (with replacement) from the original dataset.

6.1. Measurement model

As can be seen in Table 5, the composite reliabilities were above the recommended 0.70 level [27,46], whereas the average variances extracted were above 0.50 for all constructs. Hence, the instrument demonstrated adequate reliability and convergent validity. Discriminant validity was assessed by verifying that the shared variance (or squared correlation) between any two constructs was less than the average variance extracted by the items measuring the constructs [19].

6.2. Test of hypotheses

Following the confirmation of acceptable psychometric properties in the measurement model, we tested the structural model. First, the structural model was tested with the pooled dataset ($N = 266$), which did not take into consideration discrepancies in self-age perception. This analysis is what one would expect to conduct when it is assumed that cognitive age is the same as chronological age (i.e., when discrepancies in self-age perception are not accounted for). The results are presented in the first column of Table 6. The results suggest that all four antecedent constructs have significant impact on behavioral intention to use MDS. Of the four constructs, perceived ease of use and subjective norm seem to have the greatest impact.

In order to test our hypotheses, we conducted tests of the structural model with the two subgroups divided depending on whether discrepancies in self-age perception exist. The first subgroup is composed of those respondents whose cognitive age was the same as their chronological age ($N_1 = 173$) and the second subgroup was composed of those whose cognitive age was less than their chronological age ($N_2 = 93$). The results show that each subgroup exhibited differences in relationships compared to the pooled sample and that the two subgroups exhibit distinctive patterns.

In summary, three of our four original null hypotheses were rejected (H1: perceived usefulness, H3: perceived enjoyment, and H4: subjective norm). That is, cognitive age and chronological age seem to have different effects on the formation of IT acceptance intentions.

7. Discussion

In the current study, we investigated the impact of cognitive age on users' IT acceptance decision processes. A model of technology acceptance was empirically tested with MDS users of two groups: (1) a group of users who perceive themselves as younger than their chronological age; and (2) a group of users who perceive themselves to be as old as they actually are. Our findings indicate that the factors determining the behavioral intention to accept IT in each group were quite different (i.e., three of the four determinants in the model).

The observed differences in perceptions, attitudes and behaviors due to discrepancies in self-age perception are quite revealing and call for additional research on the effects of cognitive age on human behavior as we have been witnessing over the last few decades a steady growth of aging population in many nations [57]. Moreover, research shows that middle-aged people will identify themselves

Table 4
Discrepancy in self-age perception.

		Cognitive age				
		Teens	*20s*	*30s*	*40s*	*50s*
Chronological Age	*Teens*	11	32	3	1	0
	20s	5	249	82	2	0
	30s	0	42	139	11	1
	40s	0	3	39	31	1
	50s	0	0	2	7	3

Notes: Cells shaded in black [_] represent respondents whose cognitive age was the same as their chronological age ($N = 173$), whereas those shaded in gray [_] represent respondents whose cognitive age was less than their chronological age ($N = 93$).

Table 5
Properties of measurement scales.

	CR	AVE	Shared variance				
			(1)	(2)	(3)	(4)	(5)
(1) *BI*	0.96	0.93	1.00				
(2) *PU*	0.93	0.77	0.46	1.00			
(3) *PEOU*	0.96	0.85	0.52	0.34	1.00		
(4) *ENJ*	0.97	0.89	0.50	0.63	0.41	1.00	
(5) *SN*	0.97	0.91	0.50	0.51	0.37	0.58	1.00

Notes: CR = composite reliability; AVE = average variance extracted; BI = behavioral intention; PU = perceived usefulness; PEOU = perceived ease of use; ENJ = perceived enjoyment; SN = subjective norm.

Table 6
PLS results.

	Pooled sample	Subgroup 1 (Cog = Chron)	Subgroup 2 (Cog < Chron)
PU	0.122***	0.053	0.215***
PEOU	0.323***	0.256***	0.458***
ENJ	0.136***	0.079	0.198***
SN	0.272***	0.392***	0.074
Obs (*N*)	266	173	93
R^2	43.3%	40.4%	55.0%

Significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
Notes: The dependent variable (DV) is behavioral intention (BI). PU = perceived usefulness; PEOU = perceived ease of use; ENJ = perceived enjoyment; SN = subjective norm. Standardized path coefficients are reported.

with a relatively younger (cognitively) age group as they age [39]. We believe that our study has taken an important first step in demonstrating the need to examine cognitive age perception in order to better understand individual attitudes towards technologies. We end the paper by discussing managerial and theoretical implications regarding the study of technology adoption following a discussion of the limitations of the current study.

7.1. Study limitations

Several limitations of our study warrant attention. First, we conducted a review of IS literature to explore prior uses of age measures in empirical studies in the field of IS. In doing so, we focused on three leading MIS journals – *MIS Quarterly*, *Information Systems Research*, and *Journal of Management Information Systems*. Coincidently, all three journals are U.S. based and some may argue that our key findings alongside the literature review results may have critical drawbacks in terms of generalizability. However, the journals represent the global IS academic community and consequently not all the articles published in the aforementioned journals are based on data collected within the U.S., with some published studies reporting on findings using non-U.S.-based data collected from Hong Kong, Canada, Germany, Japan, Spain, and Australia among others [e.g., 9,15,20,28]. While a more exhaustive literature review should include all published IS journals in different countries and languages, this is beyond our scope and control and given that the trend of studies published in the field's leading journals represents the best work in the global IS community, our findings (literature review results, in particular) should not be viewed as biased. Additionally, although *Management Science* is considered by many to be a premier outlet for IS research, given the journal's scope that extends beyond IS research, we decided to exclude it from our systematic review. However, our review of the IS articles published in *Management Science* paints a picture that is consistent with what we present here.

Second, we examined the impact of differences in cognitive age perception in the context of adoption of mobile data services (MDS). The choice is justifiable given the increased technology trends towards personal, mobile technologies that have been termed as 'multipurpose information appliances' and enabled us to test the impact of cognitive age in a context that is consumer-oriented, but has implications as well for organizational IT users in view of the trend towards consumerized, ubiquitous enterprise information systems. Our focus on MDS is timely given the increasing demand for research that goes beyond examining the adoption of traditional information systems used specifically within organizational work boundaries [60]. In short, MDS are representative of such multipurpose information appliances that are used in both work and personal contexts. Moreover, due to the nature of the technology, MDS are used by all age groups, including the elderly, the age group within which the discrepancies between cognitive and chronological age are most prevalent [39]. Hence, this makes MDS an appropriate context within which to illustrate that models of technology adoption that consider chronological age may produce insights that are different from those that consider cognitive age. More research is warranted however in order to examine whether non-consumer oriented technologies that are mandated for use only within organizations are also affected by cognitive age.

Third, our findings are based on a survey of users of mobile data services in Hong Kong. We believe that the sample is appropriate as Hong Kong is arguably among the most technically advanced in terms of mobile infrastructure and mobile penetration in the world. However, the sample is from a single culture and thus future research may want to examine the impact of cognitive age in other cultures in order to further generalize from the research findings.

Fourth, our research model may not seem comprehensive enough to capture complicated human behaviors and/or decisions regarding technology acceptance. We need to note, however, that our research model is informed by general consensus with respect to technology acceptance decisions [59] based on the theory of planned behavior. According to the Theory of Planned Behavior (TPB) [1], which is extended from the Theory of Reasoned Action (TRA) [2], individuals form behavioral intention to engage in a certain behavior, which are influenced by: a) cognitive and affective evaluation of the behavior and its outcomes (attitude); b) normative beliefs regarding its social desirability and acceptance (subjective norm); and c) beliefs regarding the ability and opportunity to perform the behavior (perceived behavioral control). Perceived usefulness and perceived enjoyment in our own study pertains to cognitive and affective feature of attitude, respectively. Perceived ease of use in our own model is consistent with perceived behavioral control in the TPB. Finally, we also included subjective norm in the current model. With all being said, our research model should be viewed as parsimonious enough by excluding any non-critical variables and also should be viewed as comprehensive enough to include all critical variables suggested by the TPB. Subsequent studies of human behaviors have been successful in investigating other intervening variables in the basic TPB model, and future research should examine how the impact of these other variables varies as we introduce cognitive age into the model. This however, is beyond the scope of the current study and we remain focused on the impact of cognitive age in the basic TPB framework in order to stay focused on our original research goal of demonstrating the importance of considering cognitive age in order to obtain a more accurate picture of the difference in the antecedents of behavioral intentions to adopt certain technologies.

Finally, in examining the importance of understanding cognitive age in order to better understand technology adoption intentions, we focused on comparing the cognitively young (i.e., those whose cognitive age is less than their chronological age) with those whose age perception is at their chronological age. We did not examine in our research the potential differences for the cognitively old (i.e., people who perceive themselves to be older than they are). This is because our impetus for arguing for the incorporation of the cognitive age construct stems from recent trends in wider discrepancies between cognitive and chronological age among the older generation as the population ages. Moreover, the population driving IT adoption that are multipurpose information appliances used both in work and personal domains is largely consisting of the population where it is more likely that people feel cognitively older. Research in the psychology of aging has found that it is generally teenagers whose cognitive age is greater than their chronological age, with the middle and later adult year groups more likely to experience discrepancies in the opposite direction – feeling cognitively younger [39]. Furthermore, the number of survey responses in which the respondent's cognitive age was greater than his/her chronological age was too small to derive any meaningful statistical inferences ($N = 13$). Hence, we focused our research model on the cognitively young among the older population segments. Future research should examine whether technology adoption processes are also different from the cognitively old, relative to their chronological age.

7.2. Managerial implications

Our findings have implications for various facets of IT management. For example, practitioners involved in marketing of IT products/services should be able to better understand their customers. The current study clearly suggests that the concept of age is not as simple as it seems. Customers, especially those in their 30s or 40s may perceive their age differently, and such self-perceived age (i.e., cognitive age) seems to play an important role in their IT acceptance decision-making processes. As shown in our results, the typical market segmentation approaches based on chronological age will incorrectly identify the needs of the customer whose cognitive age is not identical to their chronological age, and hence may run the risk of alienating their target customer group by ignoring potential discrepancies of cognitive age. Hong and Tam [28] suggest that there is an intrinsic force from the demand side to intensify the personalization of IT products and services. In addition, the ever-increasing variety of IT products and services call for a clear necessity to refine consumer target segmentation approaches. Using cognitive age as a basis for customer segmentation and personalization can help practitioners to better understand what consumers really need.

Customer information that incorporates cognitive age should enable development of better promotion plans and overall resource allocation for marketing activities. Furthermore, the use of cognitive age in the analysis of elderly people should help improve sales from IT products and services, as more new IT products and services become available at the individual consumer market level. The global aging trend has increased the size of the elderly customer segment, a segment which shows great marketing potential due to its strong purchasing power – e.g., affluent disposable income and high spending propensity [51]. Given that the success of many IT companies relies heavily on consumer IT markets, it is critical to better understand the various needs of the elderly people. This is especially important as a growing body of research in marketing shows that consumer decisions are driven more by their cognitive age, than with their chronological age, as more baby boomers perceive themselves to be cognitively young, exhibiting a continued interest in keeping abreast of technological developments [17,18,48]. Similar arguments can be applied to the design of IT products and services. Identifying the factors that drive IT acceptance is critical for designers/developers of IT products and services [21]. As the manufacturing paradigm has shifted to mass-customization, developing IT products and services that suit various customer needs is crucial for market success. Designers can gain further insights into customers' needs through the concept of cognitive age.

7.3. Theoretical implications and future research

Prior age research suggests that defining the age of a person should not be a monolithic process [e.g.,51]. Indeed, the current study suggests that the role of age in IT acceptance processes may be dependent on how age is defined and perceived. Our results imply that cognitively young users consider different factors in their IT acceptance decisions, compared to other users, all of whom are of the same chronological age. In line with this reasoning, it would be worthwhile to empirically explore the moderating effect of cognitive age on the theoretical relationships in other IT acceptance frameworks, so as to build a more holistic view of IT acceptance processes.

Cognitive age can provide interesting future directions for research in human–computer interaction (HCI). As age is one of the most inherent and fundamental characteristics of all living organisms – especially humans, it surely embodies interpretations and implications for numerous interactions between the organisms and objects in a variety of contexts, including between humans and computers (i.e., HCI). For example, the role of cognitive age can be examined in the contexts of IT-based training and acceptance of various technological innovations in organizations. Whether IT-based training can show different degrees of effectiveness to cognitively young workers, or whether different types of user interfaces are more usable for cognitively young users are all interesting HCI issues that should be addressed in order to better prepare ourselves for an era of global aging. Finally, while we focused on the cognitive age concept in examining the impact of self-perceived age on technology adoption in this study, future research may examine whether different conceptualizations of self-perceived age, namely social or comparative age [34] and ideal or desired age [5] to yield other interesting patterns that had hitherto been undiscovered in prior research where age was treated as a simple chronological number.

Although the present study presents a seemingly simple result – that the factors influencing technology acceptance decisions depend on how age is conceptualized, this apparent simple finding has complex ramifications for many important research issues related to cognitive age, chronological age, and their role and impact in many IT management contexts. In summary, our study has highlighted the importance of age in IT acceptance decisions, and extends TAM research by introducing cognitive age as an important antecedent to behavioral intention.

Appendix 1. Research constructs and measures

Item	Scale
Behavioral intention (*BI*)	
BI1	I intend to continue using MDS in the future.
BI2	I will always try to use MDS in my daily life.
BI3	I will keep using MDS as regularly as I do now.
Perceived usefulness (*PU*)	
PU1	I find MDS useful in my daily life.
PU2	Using MDS helps me accomplish things more quickly.
PU3	Using MDS increases my productivity.
PU4	Using MDS helps me perform many things more conveniently.
Perceived ease of use (*PEOU*)	
PEOU1	Learning how to use MDS is easy for me.
PEOU2	My interaction with MDS is clear and understandable.
PEOU3	I find MDS easy to use.
PEOU4	It is easy for me to become skillful at using MDS.
Perceived enjoyment (*ENJ*)	
ENJ1	Using MDS is enjoyable.
ENJ2	Using MDS is pleasurable.
ENJ3	I have fun with using MDS.
ENJ4	I find using MDS to be interesting.
Subjective norm (*SN*)	
SN1	People who are important to me (e.g., friends, partner, colleague, family members, supervisors, and customers) think that I should use MDS.
SN2	People who influence my behavior (e.g., friends, partner, colleague, family members, supervisors, and customers) think that I should use MDS.
SN3	People whose opinions that I value (e.g., friends, partner, colleague, family members, supervisors, and customers) prefer that I use MDS.
Cognitive age (*CA*)	
CA1	I *feel* as if I am in my ___.
CA2	I *look* as if I am in my ___.
CA3	I *do* most things as if I am in my ___.
CA4	My *interests* are mostly those of a person in his/her ___.

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