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Original Research Article

Investigating Older Adults' Willingness to Invest Time to Acquire Technology Skills Using a Discounting Approach

Joseph Sharit, PhD,[1] Jerad H. Moxley, PhD,[2,*] and Sara J. Czaja, PhD[2]

[1]Department of Industrial Engineering, University of Miami, Coral Gables, Florida, USA. [2]Center on Aging and Behavioral Research, Division of Geriatrics and Palliative Medicine, Weill Cornell Medicine, New York, New York, USA.

*Address correspondence to: Jerad H. Moxley, PhD, Weill Cornell Medicine, Center on Aging and Behavioral Research, Division of Geriatrics and Palliative Medicine, 420 E. 70th St., New York, NY 10021, USA. E-mail: sjc7004@med.cornell.edu

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Abstract

Background and Objectives: Delay discounting is a common behavioral phenomenon that can influence decision making. A person with a higher discounting rate (DR) will have a stronger preference for smaller, more immediate rewards over larger, delayed rewards than will a person with a lower DR. This study used a novel approach to investigate, among a diverse sample of older adults, discounting of the time people were willing to invest to acquire technology skills across various technologies.

Research Design and Methods: One hundred and eighty-seven male and female adults 65–92 years of age participated in the study and were given presentations on 5 different technologies spanning domains that included transportation, leisure, health, and new learning. A measure of discounting was computed based on participants' assessments of how much additional time they would be willing to spend to acquire increased skill levels on each of the technologies and their ratings of importance of attaining those skill levels. Measures of participants' perceived value of the technologies, technology readiness, and self-assessed cognitive abilities were also collected.

Results: The findings indicated a significant and robust effect of lower DRs with increasing age. Higher perceived value of the technologies and higher levels of positive technology readiness predicted willingness to invest more time to learn the technologies, whereas self-assessments of cognitive abilities predicted the levels of technology skills that participants desired on the 5 technologies.

Discussion and Implications: Our findings demonstrate that for realistic decision-making scenarios related to the acquisition of technology skills, DRs decrease with increasing age, even within an older adult cohort, and that discounting is related to the perceived value of the technology. The findings also have important implications for the design and marketing of technology products for older consumers.

Translational Significance: Our findings indicate that older adults, even in the older cohorts, are willing to invest time to acquire skills related to using new technology if they perceive value in the technology, have positive attitudes related to technology readiness, and have confidence that they have the cognitive abilities needed to acquire the necessary skills. Thus, stakeholders targeting technology adoption among older adults should consider strategies to ensure older adults understand the potential value of a technology and develop training and marketing protocols that instill confidence in older adults that they can acquire the skills needed to use these technologies effectively.

Keywords: Age, Decision making, Delay discounting, Desired skill acquisition, Technology adoption, Technology readiness

When people must choose between different amounts of a reward available at different points in time, they will almost always prefer the larger reward over a smaller one if the delay to obtaining the larger reward as compared to obtaining the smaller reward is short. However, as the delay to acquiring the larger reward increases in comparison to acquisition of the smaller reward, its subjective value decreases, or is "discounted," making the smaller reward more preferable (Hardisty & Weber, 2009). Temporal or delay discounting is a pervasive behavioral phenomenon and represents the tendency for the perceived value of something to decrease as the delay in the time for its acquisition increases (Rachlin, 2006).

Practical interest in delay discounting stems from the impact it can have on decisions people make about acquiring some type of future entity or reward that can have implications for their health, well-being, and quality of life. For example, people who discount the value of improved future health to a greater extent may be less likely to change their current sedentary lifestyle and join an exercise program as compared to individuals who discount this delayed reward to a lesser extent. The same logic applies to negative outcomes. For example, people who discount adverse future environmental outcomes to a lesser extent may be more likely to decide to adopt recycling to mitigate future negative environmental outcomes. Similarly, lower discounting rates (DRs) would generally be associated with people who are more willing to accept returns on investments that take more time to accrue.

In this paper, we report findings from a study which investigated, within a large and diverse sample of older adults, decisions regarding how much time these individuals would be willing to invest to acquire higher levels of skills on technologies that could potentially improve the quality of their lives, and whether age influenced the discounting of these technological skills. In this scenario, acquiring higher levels of skills on technologies represented the reward entities, and the amount of time the individual was willing to invest in acquiring these rewards represented the "time delay" factor, though in this situation the time delay constituted an *active* (inclination to invest time) rather than *passive* (waiting for time to pass) phenomenon, as is the case in traditional experimental delay discounting studies, and thus was likely related to the motivation that may mediate cognitive effort expenditure. Our unique approach to examining these issues was not meant to directly replicate delay discounting paradigms, but to extend those paradigms as a basis for our methodology. We also examine the extent to which variables such as the perceived value of the technology, the individual's technology readiness, and self-assessment of cognitive abilities predict this type of discounting behavior in older adults.

Background: Delay Discounting Across the Life Span

Given the potential impact on decisions, an important question in the delay discounting literature concerns whether the DRs people adopt differ over the life span. To examine this issue, investigators have typically used a hypothetical monetary reward paradigm. For example, in a study including children (n = 12; M = 12.1 years), young adults (n = 12, M = 20 years), and two older adult samples (n = 12 lower-income older adults, M = 67.9 years, and n = 20 upper-income older adults, M = 70.7 years), Green et al. (1999) asked participants to make a series of choices between a hypothetical $1,000 reward available after a delay and a smaller amount available immediately. There were eight delays for the $1,000 reward, ranging from 1 week to 25 years, and 30 immediate reward amounts ranging from $1 to $1,000. For each of the $1,000 reward delays the immediate amounts were presented in both ascending and descending orders, enabling derivation of the points of indifference between present and future amounts. The findings indicated that the rate of discounting decreased as the groups increased in age. The authors interpreted the decreases in DR as consistent with evidence that risk-taking or impulsivity decreases with age (Ball et al., 1984; Deakin et al., 2004) and that the ability to delay gratification or exercise patience increases as one ages.

Using a simpler delay discounting procedure involving hypothetical monetary rewards, Bixter and Rogers (2019) similarly found that older adults (n = 50, 65–79 years of age) discounted larger (e.g., $88) delayed rewards compared with smaller (e.g., $67) sooner rewards less than younger adults (n = 50, 18–24 years of age). To examine if an age-related effect in delay discounting might be due to younger adults being more sensitive to immediate reward gratification (Reyna & Farley, 2006), half the trials had a 30-day delay to both the smaller-sooner and larger-later rewards. The older adults were found to exhibit less delay discounting than younger adults under both trial conditions, suggesting that the presence of an immediate reward was not necessary for age-related differences in delay discounting to be manifest. However, the authors did note that in comparison to the hypothetical monetary discounting study of Green et al. (1994), the delays used were relatively short (<6 months) and that the observed patterns could change if delays extended to greater time increments. Also, unlike Green et al. (1994), they found that age interacted with reward magnitude in affecting delay discounting: the younger adults exhibited higher levels of delay discounting than older adults on the smaller reward trials, but not on the larger reward trials.

One must be cautious, however, when extrapolating discounting findings from hypothetical monetary reward scenarios to more realistic decision-making situations. An important consideration is the requirement in classic monetary reward manipulations for participants to make many decisions regarding the indifference between smaller, immediate rewards and larger, more distant rewards. Some individuals, especially older people, may not want to make these decisions; for instance, they may not find it realistic to consider hypothetical monetary rewards 20 or 25 years into the future. In more realistic scenarios involving discounting a time-related variable, older individuals may exhibit a stronger bias for the present, less tolerance for the uncertainty brought about by greater delays, and a greater sensitivity to their projected free time—all of which may promote greater delay discounting behavior (Hardisty & Weber, 2009). This perspective is consistent with behavioral economic models that suggest older individuals should consider their reduced number of remaining years when making decisions, and therefore should discount delayed rewards to a greater extent than younger individuals (Sozou & Seymour, 2003). More generally, as Bixter and Rogers (2019) have noted, "discounting of one type of reward may not transfer to other types of rewards."

Unfortunately, beyond behavior involving hypothetical monetary scenarios, little is known about how increasing age affects delay discounting. Melenhorst (2002), in a study of 24 adults (12 aged 40–45 years and 12 aged 70–75 years), investigated decisions related to hypothetical delayed vacations of differing durations and locales to determine if the postponement of a desired or planned activity is more troublesome for older as compared to younger people. Two hypothetical vacations presented for each trial were delayed, at different lengths, and a discounting parameter was derived using a linear relationship between the value of the vacation locale and the delay in its receipt. Older adults displayed a higher DR than younger individuals, which Melenhorst suggested might have implications for other older adult activities and plans.

Best (2011) examined how older and younger adults discount learning needed to use and interact with technology. Participants were given hypothetical scenarios such as being taught a programming language across a set of lessons, with the reward being a percentage score on a (programming) language proficiency exam that the individual could attain and the delay (i.e., time-related) component being the number of lessons required (1–27). Best (2011) hypothesized that the older participants would demonstrate greater DRs than younger adults due to the inherent increase in the cost of any delay in learning associated with age (Charness et al., 2001). A significantly larger discount rate was found in the older adults for three of the four technology-related discounting measures.

Overall the relevant literature examining discounting behavior among older adults for more realistic, other than hypothetical monetary scenarios, is limited; the findings are mixed; involve small samples; and the age ranges of the older adult samples are largely restricted to the younger old.

Study Objectives

We present findings from a study that used a novel approach for investigating delay discounting among a relatively large and diverse sample of older adults who made decisions about acquiring different levels of skill on a set of technologies. The technologies were representative of a variety of domains, including transportation, health/wellness, and lifelong learning. We selected technologies that we determined, both in principle and based on our past findings (Berkowsky et al., 2018), had potential value in terms of enhancing quality of life. For each technology participants were asked how much additional time they would be willing to invest to achieve a particular level of skill on that technology, with the option, as in realistic contexts, of choosing not to invest any additional time beyond acquiring the adequate skill level for their needs.

Our primary objective was to determine how older adults discount the value of increased technological skill in a realistic and meaningful decision-making context across a broad older age cohort. Practically, our findings also extend knowledge regarding factors that influence technology adoption among older adults. We hypothesized, based on the importance that the technologies examined may hold for older adults in terms of enhancing independence, and past research which strongly suggests that older adults are motivated to learn new technologies that can improve the quality of their lives (e.g., Chiu et al., 2016; Czaja et al., 2018; Mitzner et al., 2010; Neves et al., 2013), that the DR would decrease with age.

A second objective was to identify variables that predict discounting behavior. The emphasis was on variables identified in the literature that might influence older adults' willingness to adopt technology such as one's attitude toward the technology (Lian & Yen, 2014), the perceived value or benefits of the technology (Berkowsky et al., 2018; Melenhorst et al., 2006), and confidence in ability to use the technology successfully (Lee & Coughlin, 2015). Thus, we examined the perceived value of the technology, attitudes toward technology, and self-assessments of cognitive abilities as expressions of confidence in one's ability to learn the technology.

We also explored gender differences in discounting behavior. Dittrich and Leipold (2014) reported that males preferred a smaller immediate payment rather than a larger delayed payment, suggesting that females generally are better able to delay gratification and demonstrate lower impulsivity in comparison to males. There is also contradictory evidence which shows that females discount more steeply than males (Reynolds et al., 2006), which is consistent with the literature on gender differences in financial risk-taking (Charness & Gneezy, 2012). Our interest was in examining gender differences in discounting the time willing to invest to acquire technology skills within an older age cohort.

Finally, we examined if discounting behavior was influenced by the type of technology as this can have important practical implications for designers and marketers of these types of products for older consumers.

Research Design and Methods

Participants

The sample included 187 adults aged 65–92 years (M = 74.1, SD = 6.3) that was primarily female (78%, n = 145), diverse in age, with 41% (n = 77) of the participants ≥ 75 years of age, and diverse in ethnicity/race; 21% (n = 40) of the participants identified as Hispanic and 36% (n = 67) identified as Black or African American. Most participants (84%) reported having at least some college education, being retired, and 90% self-reported their health as at least good. Participants were recruited from two large U.S. cities through advertisement in local media and newsletters, interactions with agencies serving older adults, and participant registries. Interested participants completed an initial telephone interview that assessed basic eligibility. Study eligibility included being 65 years of age or older; being able to read and understand English at the sixth-grade level; having no problems related to hearing (with correction), vision (at least 20/70 with correction), or arthritis; noncognitively impaired as measured by the TICS instrument (Telephone Interview for Cognitive Status; Brandt et al., 1988) with cutoff scores adjusted for age and education (e.g., for people between 70 and 79 years of age, a minimal score of 29 was required for those with less than a high school education and a minimal score of 31 was required for those with at least a high school education); and having no experience with any of the five technologies presented in the study. Participants provided written informed consent and were compensated $40.00 (and any parking expenses) for their participation. The Institutional Review Boards affiliated with the academic institutions at each site approved the study.

Procedure

To facilitate data collection, we employed a modified version of the Technology Assessment Procedure (TAP; Berkowsky et al., 2018) developed in an earlier study that examined factors influencing technology adoption among older adults. TAP is a mixed-method data collection procedure that involves presenting in-depth overviews of various technologies, completing survey questionnaires rating the technologies, and participation in postpresentation focus groups. In this study there were no focus group discussions.

Each study session involved groups of 2–4 people. Participants were introduced to the study, provided written informed consent, and then individually administered a demographic questionnaire, the WRAT (Wide Range Achievement Test; Wilkinson & Robertson, 2006) to assess literacy, and a vision test. Participants who did not meet the inclusion criteria were compensated $10 for their time.

Participants as a group were then shown PowerPoint presentations on five technologies in a predetermined random order to minimize order effects. The five technologies were: (a) Lyft, a ride-sharing app; (b) eCareCompanion, an app that allows sharing of health information with your care team, tracking of health tasks, and optional devices to measure vital statistics; (c) Curious.com, a website dedicated to providing lessons for lifelong learners on a variety of topics; (d) InteliChart, a patient portal that allows an individual to view medical charts, schedule an appointment, and manage other aspects of health care; and (e) Fittle, an app that uses a virtual coach to help people meet health and fitness goals.

Each presentation lasted about 10 min and participants were allowed to ask clarifying questions about each technology; however, there was no discussion among the participants. Following the presentation of each technology, participants completed a technology rating questionnaire to rate the technology based on a variety of criteria. This analysis focused on "perceived value," in which participants were asked to rate the importance or value (1, not at all important, to 9, extremely important) of the technology presented to them. After the participants completed the five presentations, a summary of the technologies was presented, after which participants were able to review their ratings and make changes if desired.

Instrument to Measure Time Willing to Invest to Attain Technology Skills

Two instruments were designed for assessing participants' discounting behavior. Both instruments were administered following the PowerPoint presentations and presented to each participant on a laptop computer. The first instrument, described in this section, assessed the time participants were willing to invest to acquire each level of skill on each of the five technologies. In the second instrument, participants rated the importance of each technology for each skill level; this instrument is discussed in a separate section below.

To ensure comprehension, the study facilitator, adhering to a script, described to participants as they followed on their computers, how to use the instrument for assessing the time they were willing to invest to attain technology skills. Participants were instructed to indicate, by means of a scale, how much time (using hours and minutes) they would be willing to spend to achieve a certain level of skill in using the technology in question. The instructions emphasized that the amount of time the participants believed it would actually take them to attain a level of skill was *irrelevant* to the task. Instead, the participants were instructed to only estimate how much time—which would not have to occur consecutively but could occur over some reasonable interval such as a few days or a week—they would be willing to invest to acquire that skill level, assuming no matter how large or small the quantity of time they were willing to invest they would attain that level of skill desired.

Another point of emphasis was that they did not have to achieve total mastery of a technology if that was not their need or preference. Time willing to invest amounts and importance of the technology ratings were only given for the levels of skill the participant desired to attain. The five levels of skill—basic, moderate, intermediate, advanced, and mastery—were also defined. Analogies to using a smartphone and camera were provided to clarify differences among the skill levels (Table 1).

Next, for each technology, participants were asked to indicate how much time they would be willing to spend to reach a particular level of skill beyond the basic or "default" level of skill. Participants were to presume adoption of the technology and that for each technology it would take about 15 min to achieve a basic level of skill. The constant level of time investment for basic skills was arrived through consensus among the investigators by assessing the technologies, and provided a common basis for comparing individuals in their subsequent investments of time to acquire higher skill levels.

Participants responded Yes or No regarding their desire to attain the next level in skill on a technology, and if their choice was Yes, they were also asked to indicate the additional amount of time they would be willing to invest to achieve that skill level. This rating procedure was repeated for each level of skill up to the desired level of skill for each technology. Prior to making these assessments participants were given a practice example in which they rated the time they would be willing to invest in learning to use a robot (ROOMBA) to help them perform household chores such as vacuuming the floor.

Motivation and cognitive effort

We acknowledge that despite our explicit instructions and explanations, the participant's willingness or inclination to invest time may be related in some way to the cognitive effort which would be required to reach various skill levels on the technologies. The experimental paradigms for discounting cognitive (or physical) effort typically rely on hypothetical monetary reward paradigms. For example, using an Effort Discounting Questionnaire, participants would indicate their preference of two monetary payoff alternatives: an effortless alternative in which a variable amount was to be received immediately and without effort, or an effortful alternative, in which a constant amount was to be received in 30 min following exerting a certain amount of designated effort during this time (Białaszek et al., 2017). To become familiarized with the designated types and amounts of cognitive and physical effort in the effortful alternatives, participants had already performed 20 full squeezes with a gripping device, and a total of five mathematical tasks, each consisting of adding 3 four-digit

Table 1. Descriptions of the Five Skill Levels

Levels of skill and descriptions	Analogies
1. *Basic Level of Skill*: At this level you would be able to use the technology in the most basic way.	Assume you were given a new iPhone. On the iPhone this would be the equivalent of being able to use it to call or send a text to a family member or friend. Another example would be using a camera. At this level you could turn the camera on and take a picture.
2. *Moderate Level of Skill*: You now have fully mastered the basic skills and with some additional effort can use some other general functions of the technology.	If you spend some more time and additional effort learning the iPhone you would also be able to use it to perform other basic functions, beyond texting and calling friends, such as taking pictures with the camera, searching the internet, or using the maps feature to find your way. In the camera example, you would also be able to view the photos you have taken and delete those that you do not like.
3. *Intermediate Level of Skill*: You can now easily perform all of the basic and general functions, but at this level of skill you can begin to adapt the technology to meet your particular needs or to use more functions/features.	On the iPhone you can now call, text, and use the camera, internet, and maps quite easily. At this level of skill you would be able to find and download "apps" (e.g., games of interest or weather apps), and fully use the new apps that you have downloaded. Using the camera you would be able to adjust the lens to take close-up shots or turn off the flash.
4. *Advanced Level of Skill*: You can now use almost all of the functions of the technology with ease. At this level, you would need to spend more time to learn only a few other aspects of the technology, ones that you might not use all of the time.	On the iPhone you can use all of the functions and features and are able to download and use apps. At this level you would also be able to perform advanced functions such as syncing (establish a connection) your iPhone to your car's Bluetooth system or to your home security system. Using the camera you would also be able to manually adjust the light level for a particular photo or use the video option.
5. *Mastery Level of Skill*: You have fully mastered the technology and can now explain how it operates to other people who have no experience with the technology.	You could now teach your friend or your neighbor, who has no prior experience with the technology, to use the technology. On the iPhone you can use all functions, self-troubleshoot most problems, and can teach a person how to use any function. On the camera you can use all of the functions and can teach a person as well how to use all of the functions.

numbers, for the physical and cognitive effort conditions, respectively. In the main procedure, participants made their choices until their preferences shifted from the effortless alternative to the effortful alternative, and then proceeded to new sets of comparisons.

Clearly, our methodology does not unequivocally achieve unconfounding of time willing to invest and cognitive effort, and we recognize that some amount of this confounding is natural. Having such total unconfounding is probably not even desirable from an applied perspective, and use of time willing to invest is most likely a much more accessible concept to lay people than concepts like cognitive effort or mental workload. In this regard, the willingness to invest time is consistent with the concept of cognitive effort. More conceptually, the willingness for older adults to invest time to attain skills on technologies that can meet their life goals is believed to reflect increased motivation which, in turn, can mediate the cognitive effort needed in practical situations to translate to engagement with technologies. For example, in a study using responses from the Health and Retirement Survey, Queen and Ness (2018) demonstrated that intrinsic motivation partially mediated the association between having health and cognitive resources and engagement in cognitively demanding everyday activities. The key seems to be the nature of the perceived benefits.

Instrument to Measure Importance Assigned to a Skill Level

After completing the Time Allocation instrument for each of the five technologies, participants rated (on the laptop) the importance of attaining their desired skill levels on each of these technologies using a scale that ranged from 1 to 10: a 1 indicated no importance, a 5 indicated average importance, and a rating of 10 indicated extremely important. Participants were cued (by the computer interface) to assign importance values only for those skill levels that they had previously indicated they were willing to invest time to attain. In providing these importance ratings, it was emphasized to participants that they should disregard how difficult they thought it was to gain a level of skill, and instead focus on the importance of obtaining that level of skill. To be consistent with the traditional delay discounting paradigm, participants were informed that for each technology their rating for attaining each higher skill level that they were willing to invest additional time to attain could not be lower than the prior rating, although it could stay the same as ratings of importance were cumulative. Thus, each level of skill was to be rated as including the value of all previous levels and the added value of the current level of skill.

Additional Instruments

Before the PowerPoint presentations, participants completed a Self-Assessment of Abilities questionnaire. This eight-item instrument was adapted from Ackerman and Wolman (2007) and assessed participants' self-appraisal of the following abilities on a 9-point scale (1 = very low ability, 9 = very high ability): vocabulary, comprehension, numeric ability, memory, learning ability, problem solving and reasoning, detection, and grasping/manipulative skill. Participants also completed the Technology Readiness Index (TRI 2.0), a 16-item questionnaire designed to determine an individual's predisposition to adopting new technologies (Parasuraman & Colby, 2015). The items comprise two positive dimensions: optimism (belief that technology increases control, flexibility, and efficiency) and innovativeness (one's view of being a "technology pioneer"), and two negative dimensions, discomfort (a tendency to being uncomfortable with or overwhelmed by technology) and insecurity (a general feeling of skepticism or fear toward technology). Participants were asked to what extent they agree or disagree with 16 statements across the four dimensions (1 = strongly disagree, 5 = strongly agree).

The Measure of DR

DR was measured as the ratio of the change in ratings between the importance assigned to the basic skill level and the highest skill level a participant desired to attain for a given technology (numerator) to the change in the total time that the participant was willing to invest in attaining that highest desired skill level (denominator). In computing the denominator, the constant time of 15 min prescribed for the basic skill level was subtracted.

Although there are obvious differences between traditional delay discounting tasks and the current procedure, they are conceptually similar. Consider the two following situations: (a) Focusing on the denominator, suppose that two people rate the reward for acquiring a particular skill level on a given technology the same (no difference in the numerator), but one of them would want to allocate less time to obtain that skill level. This would be analogous to the classic delay discounting hypothetical monetary reward scenario where, for example, relative to a person accepting \$100 at the present, a person with a higher DR would require a given sum, for instance \$200, sooner in time (less delay, less waiting through time) than a person with a lower DR. (b) Focusing on the numerator, suppose that two people are both willing to invest the same amount of time to attain a certain skill level, but one person attaches a greater reward value to that skill level. This would be analogous to the hypothetical monetary reward scenario where, for example, relative to accepting \$100 at the present, for a fixed time delay the person with the higher DR would want a higher reward (e.g., \$300) as compared to the person with the lower DR (e.g., \$200).

On each of the five technologies that participants evaluated, not all 187 participants indicated that they desired to attain more than the basic skill level; thus, the DR could not be computed for every participant for every technology. One hundred and sixty-seven participants had at least one DR value and 81 participants had measures of DR for all five technologies (e.g., they desired attaining more than a basic skill level on each of the five technologies). To confirm that the DR measure represented a meaningful construct we performed a principal component analysis on the results of the 81 people for whom DR values were available for all five technologies using the orthogonal promax rotation. A parallel analysis, which compares the eigenvalues from the data with those computed from noise with similar features, was used to select the number of factors, and the pairwise correlation matrix was used to estimate the model. The results of this analysis indicated that a single factor extruded 66.77% of the variance in the DR measure, with it being the only factor with an eigenvalue above 1 or, above the simulated eigenvalue from parallel analysis.

Dependent Measures and Predictor Variables

In addition to DR, three other dependent measures were examined. Two of these constituted the denominator and numerator of the measure of DR: time willing to invest to attain skill on the technology, and the importance values assigned to attaining those skill levels. Time willing to invest was computed for each technology by summing the total time participants stated they would be willing to invest across desired skill levels. Because some of the times were extremely skewed, these values were Winsorized at each skill level to increase the robustness of our estimate. Each technology, and each level of skill for each technology, was Winsorized separately. Accordingly, if a participant provided a value for the additional time willing to invest at a skill level that was more than 2 *SD*s greater than the mean level for that level of skill for that technology, we lowered their value to be equal to 2 *SD*s above the mean. As with the measure of DR, this (time) variable was log-transformed, as discussed below. The measure of importance was defined as the value participants provided (1–10) for the highest level of skill they desired to acquire for each technology. The third additional dependent measure was the level of skill desired, defined as the highest level of skill participants wished to attain for each technology (ranging from 1 for basic skills to 5 for a skill level of mastery).

The variables used to predict the four dependent measures included: age and gender; positive technology readiness (the sum of the two positive subscales, optimism and innovativeness, of the TRI), and negative technology readiness (the sum of the two negative subscales, discomfort and insecurity, of the TRI); self-assessed abilities, derived from six cognitive abilities of the eight abilities comprising the Self-Assessment of Abilities questionnaire; the perceived values participants accorded to each of the five technologies; and the type of technology (five types).

As is common with measures of time even after Winsorization the time willing to invest measure was extremely skewed and, because the measure of DR was formed from the time willing to invest, it was equally skewed. For each technology both variables showed skewness of >2, suggesting that the variables had a long right tail—which is often observed in measures of time. Values of 1 are typically considered highly skewed. These two variables were thus logarithmically transformed, which reduced the skewness substantially in all cases. The ratings of importance of the technology as well as the level of skill desired did not show skewness issues, with all ratings for all technologies being between −1 and 1; thus, they were not transformed.

In transforming the DR measure we faced the challenge that there were cases where equal importance ratings were given to each level of skill. This can be interpreted as participants indicating that while they would be willing to invest some amount of time to improve their skill to this level, our scale was not fine enough to register a marginal increase in importance. Before transformation, this meant that these cases had a DR of 0, which has an undefined logarithm. Instead of marking these values as missing, an arbitrary constant of 0.01 was added to each DR before transformation so that the lowest observed DR was −2, with −2 being the base 10 logarithm of 0 + 0.01.

Analytic Procedures

Correlations among the study variables were computed using the averages of each of the four dependent variables—DR, time willing to invest, importance value of desired skill, and level of skill desired—across the five technologies. A multilevel regression model was used to test for the effects on each of these dependent variables. The regression model accounted for the individual computed values of each of these dependent variables for each of the five technologies examined.

For each dependent variable our model treated participants as a random effect, and age, gender, the composite positive and negative subscales of the TRI, perceived value of each technology, self-assessed abilities, type of technology, and the interaction of age and type of technology as fixed effects. This multilevel model allows data with a nested structure to be analyzed at multiple levels simultaneously. Furthermore, treating participants as a random effect enables participants to vary around their own mean as opposed to the sample mean. Thus, the DR for each technology (the technology level) is nested within the individual (the individual level). In all cases the random effects were statistically significant, suggesting that the use of a random effects model is appropriate. Variables that were measured at the individual level included age, gender, technology readiness, and self-assessed abilities. In contrast, perceived value of the technology and type of technology were measured at the technology level. The model also included a cross level interaction of age and type of technology.

In each model, Lyft, the most widely known of the technologies examined, was the reference variable and all degrees of freedom were calculated using the Satterwaite Approximation (Satterwaite, 1946) so that they may vary by parameter. The model was estimated using SPSS 25 (IBM Corp, 2017) and when appropriate a Bonferroni correction was applied to prevent type I error (Aicken & Gensler, 1996).

Results

Table 2 presents the correlations among the variables. Tables 3 and 4 present the betas, t tests, and p values for the regression models for the four dependent measures; these results are summarized below. All betas presented are the unstandardized coefficient. No independent variables are transformed; thus, for instance, age is a numeric variable by year ranging from 65 to 92.

Discounting Rate

Age significantly predicted DR such that less discounting was associated with increasing age, $t(335) = -2.24$, $p = .03$, $d = -0.24$ (Table 3). DR did not vary by type of technology, $F(4,523) = 0.82$, $p = .52$, $\eta^2 = 0.01$, nor by the interaction of age and type of technology $F(4,520) = 0.25$, $p = .91$, $\eta^2 = 0.001$. The scatterplot depicted in Figure 1 shows the relationship between age and DR for each of the five technologies.

Time Willing to Invest

Being older predicted participants' willingness to invest more time to attain greater skill on the technology, $t(430) = 2.00$, $p = .046$, $d = 0.19$ (Table 4). In addition, higher perceived value of the technologies, $t(869) = 11.86$, $p < .001$, $d = 0.80$, and higher levels of positive technology readiness, $t(186) = 2.42$, $p = .02$, $d = 0.35$, predicted willingness to invest more time to learn the technologies, but self-assessed abilities did not. The effect of type of technology was also significant $F(4,743) = 6.81$, $p < .01$, $\eta^2 = 0.01$. Further analysis using a Bonferroni corrected p value of .05 indicated that participants were more willing to invest time in Curious.com than the other technologies, specifically, than eCare Companion, $t(740) = 2.93$, $p = .003$, $d = 0.22$; Fittle, $t(746) = 4.98$, $p < .001$, $d = 0.36$; InteliChart, $t(741) = 3.34$; $p = .001$, $d = 0.25$; and Lyft, $t(739) = 3.56$, $p < .001$, $d = 0.26$. The interaction of age and type of technology was also significant, $t(740) = 2.98$, $p = .02$, $d = 0.22$; older participants were less willing to invest time in Fittle, $t(741) = -2.37$, $p = .02$, $d = -0.17$, and in InteliChart, $t(739) = -2.59$, $p = .01$, $d = -0.19$, as compared to Lyft.

Importance Value

The perceived value of the technology predicted the value of importance participants ascribed to attaining skill on the technology, $t(909) = 15.30$, $p < .001$, $d = 1.01$, as did higher levels of positive technology readiness, $t(187) = 3.08$, $p = .002$, $d = 0.45$ (Table 4). The effect of type of technology was also significant, $F(4,741) = 5.98$, $p < .001$, $\eta^2 = 0.03$, with further analysis using a Bonferroni corrected p value of .05 indicating that participants gave significantly greater importance to acquiring skill on Curious.com as compared to eCareCompanion, $t(736) = 3.80$, $p < .001$, $d = 0.28$, and Fittle, $t(745) = 4.11$, $p < .001$, $d = 0.30$. The interaction of age and type of technology was also significant, $t(736) = 2.56$, $p = .04$, $d = 0.19$, which was attributed to people who were older assigning values of lesser importance to attaining skill on eCareCompanion, $t(735) = -2.90$, $p = .004$, $d = -0.21$, and InteliChart, $t(739) = -2.40$, $p = .02$, $d = -0.18$, as compared to the reference variable of Lyft.

Level of Skill Desired

Both higher perceived value of the technology, $t(878) = 11.74$, $p < .001$, $d = 0.79$, and higher levels of

Table 2. Correlations Among the Study Variables ($n = 187$)

Variable name	1	2	3	4	5	6	7	8	9	10
1. Age	1.00									
2. Female	−0.03	1.00								
3. Positive TR	−0.02	−0.09	1.00							
4. Negative TR	0.01	−0.07	−0.17*	1.00						
5. Average perceived value	0.03	0.10	0.35**	−0.12	1.00					
6. Self-assessed abilities	−0.09	−0.14	0.30**	−0.03	0.02	1.00				
7. Average discounting rate	−0.18*	−0.14	−0.03	0.04	−0.09	0.07	1.00			
8. Average time willing to invest	0.12	0.03	0.23**	−0.06	0.38**	−0.02	−0.20**	1.00		
9. Average value of attaining skill	−0.11	0.05	0.36**	−0.11	0.56**	0.11	0.10	0.61**	1.00	
10. Average level of skill desired	0.01	−0.09	0.32**	−0.05	0.41**	0.18*	0.02	0.71**	0.66**	1.00

Notes: TR = technology readiness.
*$p < .05$. **$p < .01$.

Table 3. Multilevel Regression Models Predicting Discounting Rate and Level of Skill Desired

	Discounting rate			Level of skill desired		
Variable name	Beta	*t* test	*p* Value	Beta	*t* test	*p* Value
Demographics						
Age (centered)	−0.009	−2.24	.03	0.025	1.57	.12
Female	−0.08	−1.55	.12	−0.245	−1.31	.19
Dispositional factors						
Technology readiness: positive	>−0.01	−1.11	.27	0.040	2.63	.01
Technology readiness: negative	>−0.01	−0.04	.97	>−0.01	0.18	.86
Perceived value	>−0.01	−0.02	.99	0.230	11.74	<.01
Self-assessed abilities	0.009	0.51	.61	0.100	1.53	.13
Type of technology						
Curious.com	0.027	1.16	.25	0.277	2.77	.01
eCareCompanion	0.009	0.38	.70	−0.011	−0.11	.91
Fittle	>−0.01	−0.14	.89	−0.197	−1.91	.06
InteliChart	0.032	1.34	.18	0.053	0.53	.60
Interaction of technology and age						
Curious.com × Age	>−0.01	−0.03	.98	−0.011	−0.69	.49
eCareCompanion × Age	>−0.01	−0.11	.91	−0.020	−1.23	.22
Fittle × Age	−0.003	−0.76	.45	−0.040	−2.50	.01
InteliChart × Age	0.001	0.24	.81	−0.040	−2.52	.01

Table 4. Multilevel Regression Models Predicting Time Willing to Invest and Importance Value of Skill Attained

	Time willing to invest			Value of skill attained		
Variable name	Beta	*t* test	*p* Value	Beta	*t* test	*p* Value
Demographics						
Age (centered)	0.011	2.00	.046	0.020	0.63	.53
Female	0.004	0.07	.95	0.18	−0.56	.18
Dispositional factors						
Technology readiness: positive	0.013	2.42	.02	0.08	3.08	<.01
Technology readiness: negative	−0.001	−0.23	.82	−0.011	−0.43	.67
Perceived value	0.078	11.86	<.01	0.636	15.30	<.01
Self-assessed abilities	−0.016	−0.70	.49	0.066	0.59	.56
Type of technology						
Curious.com	0.119	3.57	<.01	0.331	1.50	.13
eCareCompanion	0.021	0.63	.53	−0.509	−2.32	.02
Fittle	−0.051	−1.49	.14	−0.594	−2.62	.01
InteliChart	0.007	0.22	.83	−0.046	−0.21	.83
Interaction of technology and age						
Curious.com × Age	−0.001	−0.23	.81	−0.049	−1.32	.19
eCareCompanion × Age	−0.004	−0.69	.49	−0.103	−2.90	<.04
Fittle × Age	−0.013	−2.37	.02	−0.042	−1.19	.23
InteliChart × Age	−0.014	−2.59	.01	−0.045	−2.40	.02

positive technology readiness, $t(186) = 2.63$, $p < .01$, $d = 0.39$, significantly predicted participants wanting to reach a higher level of skill (Table 3). Although self-assessed abilities was not significantly predictive of level of skill desired, it did demonstrate its strongest effect for this dependent variable, $t(181) = 1.53$, $p = .13$, $d = 0.23$. Type of technology was significant, $F(4,744) = 5.59$, $p < .001$, $\eta^2 = 0.03$, with further analysis using a Bonferroni corrected p value of .05 indicating that participants desired attaining a higher skill level for Curious.com than Fittle, $t(746) = 4.43$, $p < .001$, $d = 0.23$, and EcareCompanion, $t(740) = 2.87$, $p = .004$, $d = 0.21$. The interaction of age and type of technology was also significant, $t(740) = 2.48$, $p = .04$, $d = 0.18$, with older participants showing a lesser desire to attain higher levels of skill for Fittle, $t(741) = 2.50$, $p = .01$, $d = 0.18$, and for InteliChart, $t(739) = 2.52$, $p = .01$, $d = 0.19$, as compared to Lyft.

Figure 2 depicts the model-estimated means for each of the four dependent measures across each of the five technologies. Figure 3 displays partial regression plots depicting the relationships between the dispositional variables of perceived value and positive technology readiness with each of the two dependent measures comprising the measure of DR: time willing to invest and importance value. Figure 4 shows the relationship between participants' willingness to invest time to attain desired skill levels and the level of skill they desired for each technology.

Discussion and Implications

Delay discounting is a common behavioral phenomenon that has an influence on decisions people make in a variety

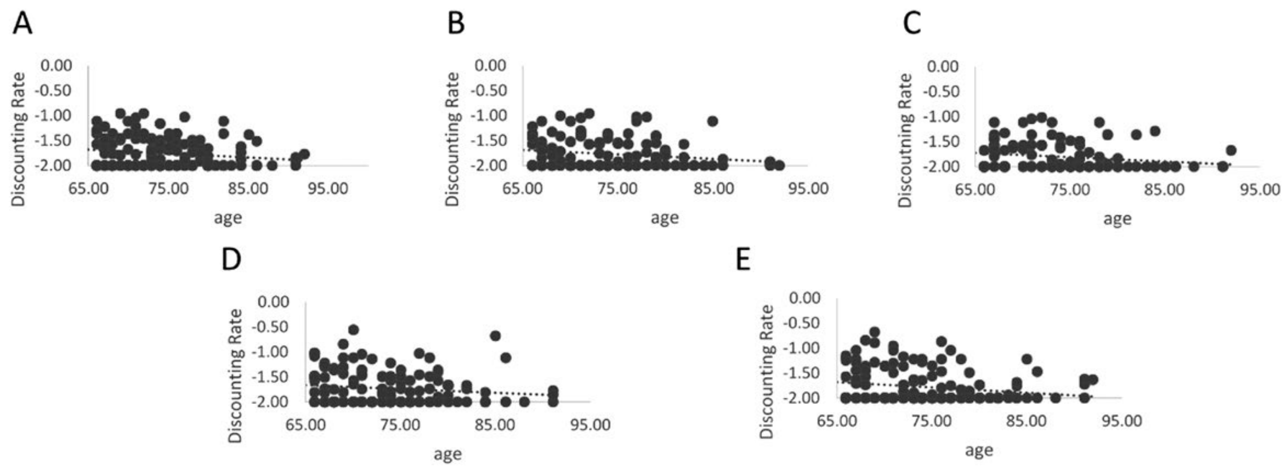

Figure 1. Relationship between discounting rate and age for each of the five technologies: (A) Curious.com, (B) eCareCompanion, (C) Fittle, (D) InteliChart, and (E) Lyft.

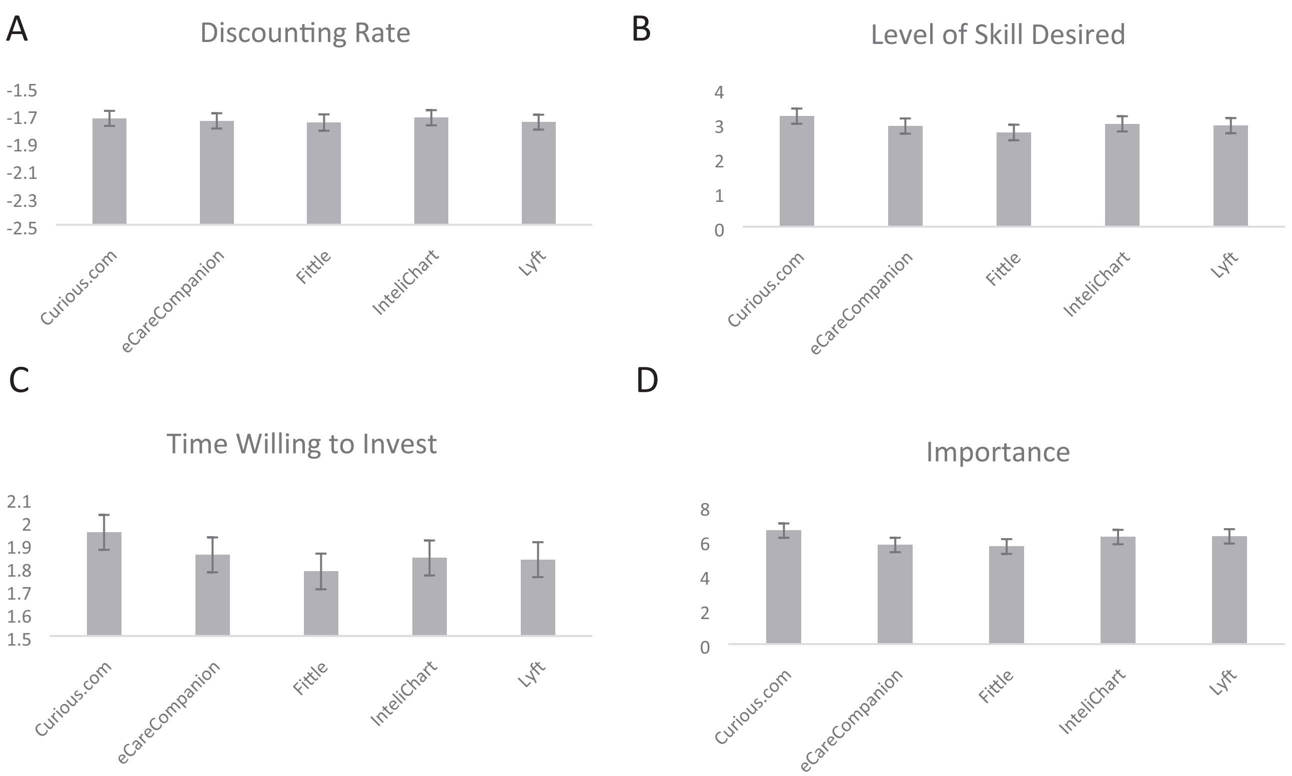

Figure 2. Model-estimated means across the five technologies for each of the four dependent measures: (A) discounting rate (log measure), (B) level of skill desired, (C) time willing to invest (log measure), and (D) importance value. Error bars are model-estimated 95% confidence intervals.

of contexts. Currently, findings regarding the effects of age on delay discounting are mixed. To further explore this issue, in this study a novel approach was used to investigate discounting among a relatively large sample of older adults. Using realistic scenarios, we examined the decisions that these older adults made regarding their willingness to invest time to acquire varying levels of skills on technologies that could improve the quality of their lives. The technologies spanned a range of domains that included transportation, leisure, health, and new learning. In our approach to the delay discounting paradigm, the "reward amounts" that were considered were the assessments of importance associated with acquiring increasing degrees of skill levels on these technologies, while the time "delay" factor was the time one was willing to invest to acquire those skill levels. The measure of DR was the ratio of these two components. Therefore, unlike hypothetical monetary reward scenarios, it could not, and realistically should not be computed for those situations where someone is not willing to invest time to exceed a basic—which in our case was the default—level of skill.

Our study demonstrated decreased discounting with increasing age in a realistic scenario, using a sample that was relatively large and exclusively composed of older adults with an age range of 65–92 years. Also, as compared to conventional delay discounting studies that rely on hypothetical monetary rewards, there is a unique and important difference in how the dimension of time is characterized in our scenario. In our study, the relationship between the individual and time is more *active*—the individual must consider how much of it to invest to attain desired technology skills. In conventional delay discounting scenarios, the relationship between the individual and time is strictly *passive*—the individual must consider how long to wait to accrue a larger monetary reward. This study, therefore, provides evidence that among the older cohorts, increasing age was associated with decreased rates of discounting in a scenario that involved willingness to invest time, where these time investments are believed to positively reflect intrinsic motivation, which, in turn, can mediate the cognitive effort needed to support technology adoption. This finding was robust; age was the only variable to predict DR significantly and did so in the presence of other variables.

Behavioral economic models emphasize that older individuals consider their reduced number of years remaining when making decisions, which translates into increased discounting of delayed rewards compared to younger individuals (Sozou & Seymour, 2003). These models are apt to apply to situations where there are extensive delays in receiving rewards, such as learning a new language late in life, which could conceivably take many months or years. These types of time demands are unlikely to come into play for the "everyday" technologies considered in this study, where the needed time investments to acquire a new skill are reasonable, practical, and do not extend over a long-time horizon.

Our findings also suggest that the tendencies for decreased impulsivity and increased patience are not restricted to "younger" older adults but are manifest across a broad range of older ages. As noted, this may be because the time investments were related to rewards that appeared to be reasonable and useful. Our findings provide support for this conjecture: two of the three dispositional factors examined—ratings of the perceived value of each technology and positive technology readiness—were found to be strong predictors of time willing to invest and desired skill level. Other studies have also shown that among older adults the perceived value of a technology is an important predictor of willingness to adopt that technology (Berkowsky et al., 2018; Melenhorst et al., 2006). A positive attitudinal disposition toward technology has also been found to be an important driver of usage of technology by older adults (Sharit et al., 2019). Interestingly, findings in the delay discounting literature indicating that larger delayed rewards are discounted less steeply than smaller rewards (e.g., Benzion et al., 1989; Myerson & Green, 1995) are consistent with our findings that higher perceived value of the technology predicted greater willingness to invest time (Table 2). Overall, our findings suggest that our participants may have been willing to invest time to acquire skills to use the technologies because they perceived the technologies as valuable and believed the technologies could enhance performance of important tasks.

In contrast, the self-assessment of cognitive abilities dispositional factor was not predictive of any of the dependent variables in the presence of the other model variables. However, it significantly correlated ($p < .05$) with level of skill desired (Table 2). This is intuitive as a higher assessment of one's cognitive abilities is likely to provide greater confidence that one could attain, and possibly find uses for, higher skill levels (Lee & Coughlin, 2015).

Although the analytic model did not demonstrate a significant effect of gender for any of the four dependent variables (Tables 3 and 4), after age it showed the strongest effect on DR ($p = .12$) with females demonstrating a pattern of lower discounting than males. The literature on gender differences in discounting monetary rewards is mixed; however, the trend in our findings appears to be in line with those from Dittrich and Leipold (2014) that reported steeper discounting for males compared to females. That finding could possibly be attributed to lower impulsivity among females and a greater tendency to delay gratification in comparison to male individuals. Charness and Gneezy (2012) reported that studies on risk-taking in investment consistently find that females invest less and appear to be more financially risk averse than males. Our study, however, did not address discounting from the standpoint of risk averseness in financial investments, but rather from the willingness to invest time to increase skills that can translate into meaningful improvements in quality of life. In this regard, older females may be less averse to such investments than older males. However, more research is

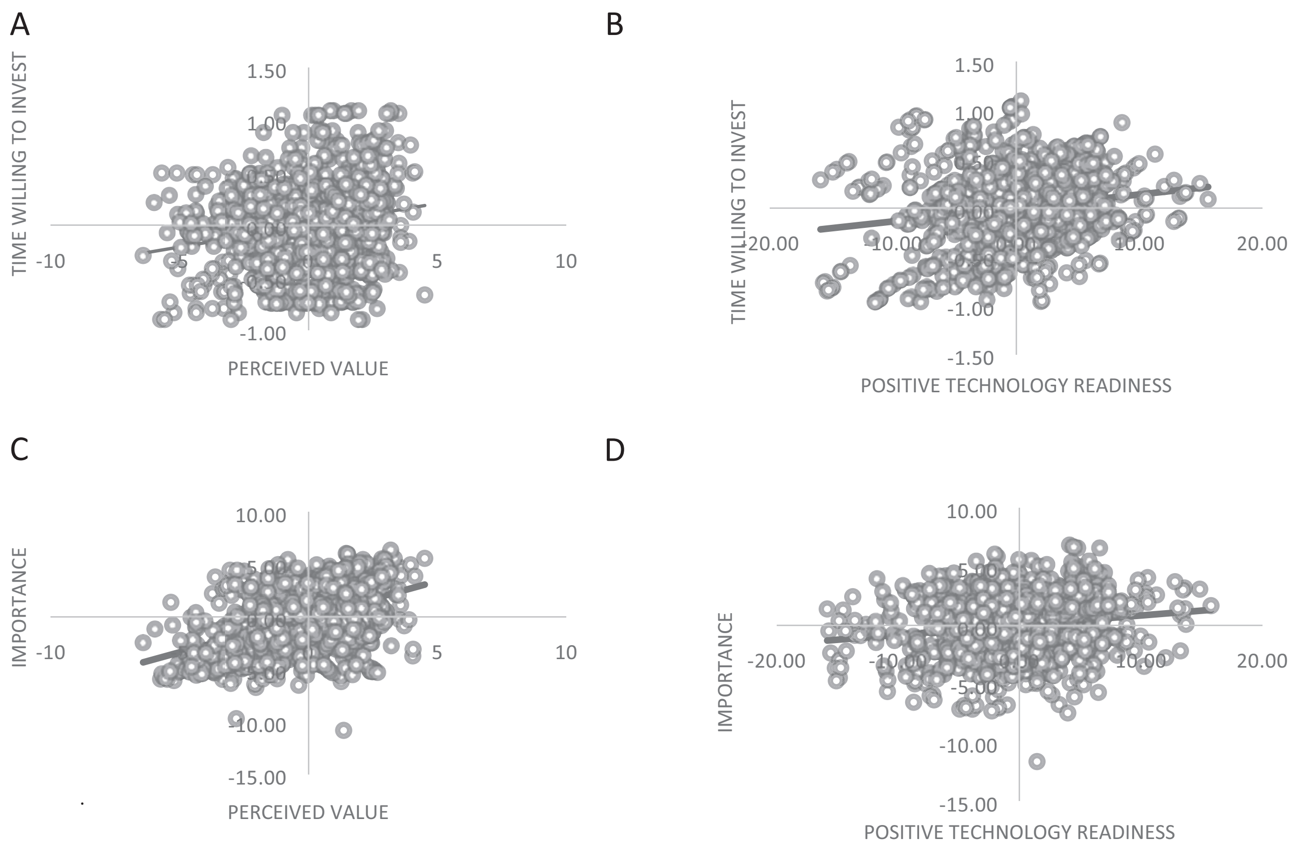

Figure 3. Partial regression plots showing the relationship of the residuals of: (A) perceived value and time willing to invest, (B) positive technology readiness and time willing to invest, (C) perceived value and importance values, and (D) positive technology readiness and importance value after controlling for the effects of the other variables modeled (see Table 3 and 4 for complete list).

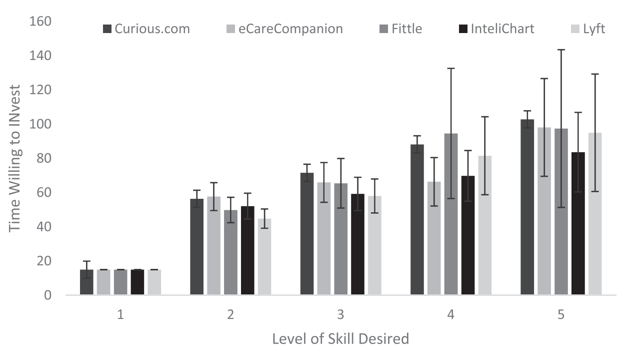

Figure 4. Time (in minutes) willing to invest for each level of skill desired by technology. Error bars = 95% confidence intervals. The five levels of skills indicated by participants that they desired were basic (1) (default time was specified as 15 min), moderate (2), intermediate (3), advanced (4), and mastery (5).

needed to examine gender differences in discounting in realistic decision-making scenarios.

Our findings also indicated that discounting behavior was sensitive to the nature of the technology. In particular, Curious.com, a website promoting lifelong learning, proved consistently superior to the other technologies with respect to the time participants were willing to invest to acquire skill, the importance values they attributed to acquiring these skills, and to the level of skill they desired to attain on the technology. This finding also underscores the fact that aging adults value opportunities for new learning and cognitive engagement. Similarly, the transportation application Lyft, which was perceived as more desirable among the older participants, may have been viewed as functionally very useful yet not unwieldy to learn. In contrast, Fittle, whose focus was on helping people reach health and fitness goals through a virtual coach that assigns daily tasks, was the least desirable based on these measures. This is consistent with data suggesting that currently a relatively low percentage of older adults engage in recommended levels of physical activity (Centers for Disease Control and Prevention, 2017). Also, the findings for InteliChart, a patient portal that assists people with the ability to self-manage their health through online access to health care information, indicated that it consistently fared worse on these measures with increasing age. Given the importance of physical activity and health management for older adults, these findings highlight the need for more effective strategies to motivate older users to invest effort in learning these types of technologies, including better marketing, appropriate training strategies, and friendlier user designs (Czaja et al., 2019). For example, problems with usability have contributed to the relatively low uptake of patient portals (Czaja et al., 2015; Heath, 2018).

In conclusion, using a novel method for capturing how individuals discount the time they are willing to invest to acquire increasing levels of skills on technologies, our data robustly demonstrated decreased discounting with increasing age within a relatively large and diverse sample of older adults. We suggest that the increased inclinations to invest more time to acquire greater skills with increasing age is related to decreased impulsivity (greater patience) with increasing age, recognition of the benefits that the technologies examined may provide in enhancing independence and quality of life, and the belief that the investments in time to acquire greater skills are reasonable. Our findings challenge the stereotype that older adults, including older females, are technophobic and unwilling to learn new skills, and instead correctly portray aging adults as an enthusiastic and demanding consumer group (Lee and Coughlin, 2015) that are willing to invest time to acquire skill needed to use technologies perceived as valuable. The findings also emphasize that product developers and marketing firms should view aging adults, including those in the older cohorts, as active users of technology and more carefully consider their needs and preferences in design and marketing strategies, especially given older adults' consumer power (Irving, 2018). It is also critical to develop strategies to enhance technology skills among aging adults given the increased reliance on technology for most activities, and to carefully consider usability issues during product design.

Limitations

Our study sample, though diverse and relatively large, was fairly well educated; thus, there needs to be caution when generalizing these findings to less educated individuals. Further, the sample was largely female; thus, the findings regarding gender should also be viewed with caution. Finally, we used a 10-point rating scale to rate the importance of the skill levels that could be attained on the technologies. It is possible that a different scale may have resulted in greater sensitivity for this construct.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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