Personal characteristics and the law of attrition in randomized controlled trials of eHealth services for self-care

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Objective Contribute to understanding of determinants of attrition in Randomized Controlled Trials (RCTs) on eHealth services for self-care and to developing a strategy to attend to them. **Background** RCTs are considered the "gold standard" in empirical research on medical interventions. However, RCTs of eHealth services for self-care are often faced with Eysenbach's Law of Attrition; that is, the phenomenon of people dropping out of the study early or being unavailable for follow-up studies. **Methods** We investigated the effects of personal characteristics on the number of days people partook in a study on the use of an online lifestyle diary with a personal computer assistant. **Results** When we assessed four stages of attrition (i.e., First Glimpser, Early Dropout, Late Dropout, Maintainer) among participants aged 21 to 65, personality (i.e., locus of control), cognitive abilities (i.e., vocabulary), and motivation to perform self-care were important determinants of attrition. **Conclusions** These data suggest that both future RCT designs and the eHealth services used during the trial should attend to these determinants. These data have particular relevance to the design of RCTs with older adults given the role of personal characteristics that affect technology use amongst older adults (e.g., cognitive abilities and personality). **Applications** Establishing and attending to determinates of attrition in RCTs of eHealth.

Keywords: health care, personal health record (PHR), personal computer assistant

Despite its evident advantages, applying a Randomized Controlled Trial (RCT) to evaluate Information and Communication Technology services for self-care (i.e., eHealth) may have limitations. For medical intervention research, an RCT is generally considered the 'gold standard' and could well be used for empirical research of eHealth[1]. RCTs determine whether a cause-effect relationship exists between an intervention and an outcome, as well as assessing the cost effectiveness of the intervention. Accordingly, findings in the experimental setting can be directly translated into implications for health care contexts. However, these trials often face a high dropout rate of participants. The phenomenon of recurring high dropout rates across RCTs evaluating eHealth services is referred to as Eysenbach's 'Law of Attrition'[2]. The Law of Attrition occurs in non-technical RCTs[3,4] and specifically in RCTs to evaluate eHealth services that support self-care. Such services enable individuals to make decisions and perform activities together with families, and communities to prevent disease, limit illness, and restore health at home[5].

The Law of Attrition for eHealth development research will likely lead to the following methodological constraints. First, shortened duration leads to low statistical power for the analysis. Second, if participants refrain from completing the presented surveys there are missing data. In turn, these constraints hinder establishing the effects of eHealth and eliciting advantages and disadvantages and possible directions for further improvement. The end result is that researchers may regard their studies as failures and frequently decide not to publish their findings at all[2].

Instead of devaluing findings of RCTs of eHealth services for self-care, a better strategy would be to measure, analyze, and discuss the determinants of attrition specifically in eHealth research[6]. Therefore, our focus was to identify determinants of attrition in an RCT that was conducted to measure the effects of a personal computer assistant on use of an online lifestyle diary. Our goal was also to determine potential strategies to cope with attrition in the future.

Attrition and determinants

In their 1999 study, Davis and Addis[7] reviewed attrition predictors for outpatient behavioral medicine treatments for headache, pain, stress, and weight management. They applied a classification of dropouts consisting of three groups: no shows (i.e., those who do not proceed to the consent or treatment stage and do not complete assessments); early dropouts (i.e., those who drop out relatively early from a program and complete a small number of assessments); or late dropouts (i.e., those who drop out after additional sessions or modules). This classification proved to be a useful starting point for defining attrition groups in RCTs on eHealth services for self-care. We expanded the categories into the following, which will be later described in depth: First Glimpser, Early Dropout, Late Dropout, Maintainer.

When establishing possible determinants for attrition, it is important to bear in mind that RCTs are typically efficacy studies. They are designed to show whether an intervention leads to the desired clinical outcome under optimal conditions. This type of trial requires control of as many confounding variables as possible[8]. eHealth aims to support self-care (i.e., focusing on individual decisions and activities) thus realizing these optimal circumstances depends greatly on personal characteristics. Moreover, what is optimal from an eHealth developer or researcher's point of view may not reflect the view of the individual performing self-care. Accordingly, it is important to gain insight into how personal characteristics explain the variance in attrition in eHealth RCTs. Such assessments must include individuals of varying age and experience as eHealth users will not only be younger adults.

Various studies have shown the influence of personal characteristics on the use of technology, including eHealth services for self-care. Demographic factors and health conditions affect the use of technology, both in the short and long term. Specifically, women, younger adults, people with higher education, and patients with more severe complaints of their illness have a stronger tendency to use self-care supporting technology[9,10,11]. Therefore, we hypothesized that these factors that impact the use of technology will also impact attrition in RCTs evaluating the technology.

Czaja[11] and colleagues reported that education level and age were predictive of technology use which accordingly, predicted breadth of computer use. Their research showed that computer and technology use was related to fluid and crystallized intelligence. Fluid intelligence is the use of deliberate and controlled mental operations to solve novel problems (e.g., processing speed), whereas crystallized intelligence is general and cultural knowledge that is incorporated by individuals through a process of acculturation (e.g., vocabulary and oral fluency)[12]. Higher scores on fluid intelligence and crystallized intelligence led to broader use of computers and other technology[13]. Thus, studies with eHealth need to attend to this variance in use related to abilities.

Personality factors also affect technology use and change as people grow older. For example, Campbell and Nolfi[14] observed a relationship between locus of control (i.e., the extent to which someone allocates events to internal or external factors) and the use of the Internet for self-care. People who scored higher on locus of control (i.e., had a stronger internal locus of control) used computers more frequently for self-care. Personality factors were also assessed by Launder and Lounsbury[15] to determine influence of the Five Factor model on internet use. The five factors are Openness (inventive/curious vs. consistent/cautious), Conscientiousness (efficient/organized vs. easy-going/careless), Extraversion (outgoing/energetic vs. solitary/reserved), Agreeableness (friendly/compassionate vs. cold/unkind), and Neuroticism (sensitive/nervous vs. secure/confident). They found that Internet use was negatively related to conscientiousness, extraversion, and agreeableness.

Personality changes throughout a person's life. A study of approximately 133,000 participants shows that Conscientiousness and Agreeableness increased throughout adulthood at varying rates whereas Neuroticism declined among women at a later age, but did not change among men[16]. Also, as people grow older, their locus of control becomes more external, specifically with respect to intelligence and health[17].

Aim of study

To test our hypothesis that personal characteristics are determinants of attrition in RCTs of eHealth services for self-care, we assessed the effects of personal characteristics (i.e., demographics, cognition, personality traits) on variance in dropout during the study[18]. Accordingly, our research question was: How does variation in personal characteristics affect participants' tendency to drop out at different stages of RCTs of eHealth services? The outcome serves as a test and extension of the Law of Attrition to eHealth studies. Understanding the differences between attrition stages in relation to personal characteristics can provide insights into their usage patterns, the potential short-term benefits of eHealth applications, and the design issues that would need to be remedied for successful adoption of systems for long-term use.

To answer this research question, we analyzed the effects of personal characteristics on attrition in a RCT of an online lifestyle diary, DieetInzicht[19], for self-care for individuals who ranged in age from 21-65. This sampling allowed a range of ages with a mean in the middle-age. All participants had computer experience. We assessed the different proposed categories of attrition (i.e., First glimpser, Early dropout, Late dropout, Maintainer) and the degree to which personal characteristics differentiated these groups. These data have implication for future eHealth trials and further development of eHealth services.

Method

Participants

Over a period of three months, we recruited 191 Dutch overweight adults, who had no previous experience with the DieetInzicht website[19] and were not under treatment with a specialist at a hospital. People are considered healthy when they have a BMI between 18.5 and 25 kg/m² and are considered overweight when they have a BMI between 25 and 30 kg/m². A BMI above 30 kg/m² is considered obese. Accordingly, we only recruited people with a BMI between 25 and 30 kg/m^2. They were recruited through the Netherlands Organization for Applied Scientific Research (TNO) participant database with overweight people and an advertisement in an online Dutch national newspaper, which ran for one week.

Of the 191 participants, 118 subjects completed their diary for at least 5 days and were included in the study. The final sample consisted of 21 male and 97 female participants, between the ages of 21 and 65 (M=43, SD=11.55). The average BMI was 27.90 (SD=2.42). Participation was voluntary. There was no individual compensation, but among the participants who fulfilled the study, 5 prizes, worth 150 Euro each, were administered by lottery. The study protocol was approved by the Dutch Medical Ethical Testing Commission (METOPP). Following the randomized controlled trial, the participants were autonomously assigned, double blinded, to the study group or control group. The latter filled in the diary and set personal goals, but did not have an assistant that provided feedback.

Procedure

The RCT assessed support of a persuasive computer assistant for use of an online lifestyle diary[18]. Foremost, we wanted to conduct research based on longitudinal data from people for whom the intervention was personally relevant. The RCT used an existing PHP and MySQL based lifestyle diary called DieetInzicht[19].

The diary helps users to obtain better insights on how to maintain a healthy lifestyle, without external manipulation. The users create a personal account with username and password. Next, they can set their personal self-management goals regarding diary use, diet, and exercise. The diet page enables users to keep a diary of the amount of products consumed (*Figure 1*). Each user keeps a diary of exercises performed on the activity page. In the report page, they receive a summary of nutrition components consumed, including, calories, fats, proteins, and carbohydrates, and number of calories burned during their activities.

In the DieetInzicht lifestyle diary, we implemented a persuasive computer assistant. The assistant offered support by monitoring the personal goals, the diary entries, and providing feedback indicating whether participants were fulfilling their goals. When providing feedback, the computer assistant followed principles of the motivational interviewing method[20]. Motivational interviewing is an effective therapeutic approach that focuses on social functioning by discussing problems and giving feedback in the form of advice and direction[21]. In accordance with the motivational interviewing principles, the computer assistant: (i) Expressed empathy: The assistant was mindful that the participant might have other priorities ("You were not successful in achieving your goal for today. Maybe you have been busy"); (ii) Was cheering and complimenting: The assistant congratulated the participants when goals were achieved ("Well done! You are successful in achieving today's goal"); (iii) Explored discrepancies between life style goal and current lifestyle: To give a good overview of the situation, the assistant indicated what goals were not realized and suggested how this could be improved ("You were not successful in achieving your goal for today. Too bad. But do not get discouraged and try again tomorrow"); and (iv) Supported self-efficacy and optimism: The assistant stayed optimistic about achieving goals and under-

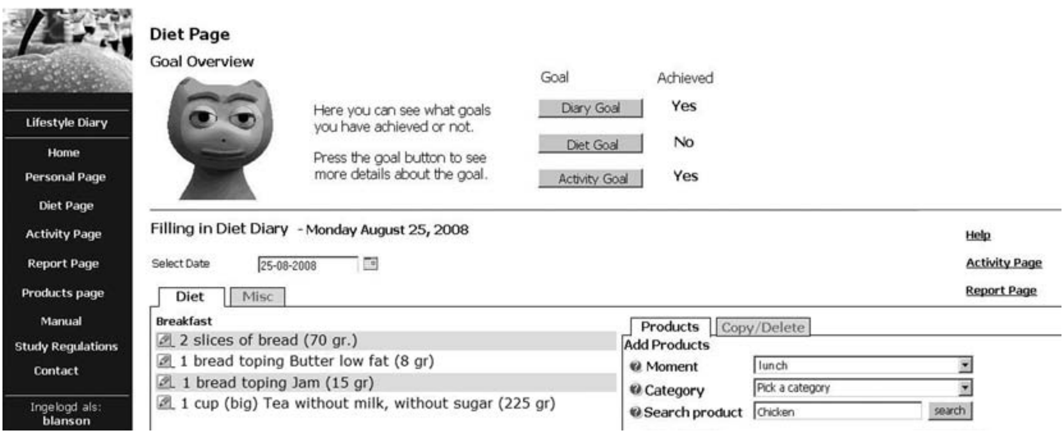

Figure 1. Interface of the online lifestyle diary with the personal computer assistant in the top left corner

Table 1. Number of participants who completed the surveys (n=185)

Survey	Pre-study (Day 1)	Study (Day 1-27)	At exit (Day 28)
Demographics	118	-	-
Computer experience	118	-	-
Locus of control scale	118	-	-
Vocabulary	118	-	-
Lifestyle knowledge	118	-	35
Motivation	118	50(Day 14)	35
Body Mass Index	118	-	35
Daily diet and physical activities	-	118	-
Online diary evaluation	-	-	35

lined that it is acceptable to make errors and the participant has the ability to realize goals ("You were not successful in achieving your goal for today. This is not terrible. It takes small steps, so keep trying in the coming days").

When someone did not succeed in attaining a goal, the assistant gave suggestions on how to achieve goals in the future by referring to relevant pages on healthy lifestyle websites, such as the Voedingscentrum, the Dutch association for nutrition[22]. Moreover, both the personal lifestyle goals and the feedback were developed by an independent dietician from Leiden University Medical Center (LUMC).

The assistant was represented by an animated iCat (*Figure 1*), which showed three facial expressions: neutral, happy and sad. These facial expressions can contribute to the understanding of the computer assistant[23] and can enrich the experience of empathy by the assistant[24]. In our study, upon the opening of the website, the assistant looked neutral; blinked its eyes, and occasionally looked around. When the user clicked on the goal buttons, the assistant provided feedback as described above and gave a happy or sad look depending on whether the person was achieving the goals or not. The iCat is a research platform created by Philips for studying human-robot interaction. It is a yellow cat with a face and a body, which expresses emotions by moving its lips, eyebrows, eyes, eyelids, head, and body[24].

Participants could directly visit the website of the online lifestyle diary and register for the study. First, participants signed a digital waiver of consent and completed a pre-test survey, which took approximately 30 minutes. Then, they were asked to set personal goals. Also, they could start filling in their dietary and physical activities per day. Filling in one day took 10-15 minutes. The first three days after signing in, participants were free to explore the website and adjust their goals. Then, participants received an email instructing them to choose three lifestyle goals, one each for the diary, diet, and physical activity, for the remainder of the study. On days 14 and 28 of the study, participants received a survey, taking respectively 5 and 15 minutes (*Table 1*).

Measurements

Participants started the study by completing an online survey concerning demographics, BMI, and computer experience (i.e., participants were asked to assess their computer skills: low, never using the computer; average, sometimes using a computer; above average, using a computer daily; professional, computer expert with programming skills). Also, they completed a survey on self-management motivation[25].This survey addressed their expectation to be able to use the diary and to maintain a healthy lifestyle. Furthermore, they completed the locus of control scale test, which measured a predominantly internal locus of control (i.e., attribute events to their own control) versus a predominantly external locus of control (i.e., attribute events to external circumstances)[26]. Finally, they completed a vocabulary test (Dutch translation of Shipley Institute of Living Scale[27]), and lifestyle knowledge test. The latter was specifically designed for our study by a LUMC dietician; to our knowledge such a lifestyle knowledge questionnaire was not available at the time of the study. An exemplary question of the lifestyle test was "For people who want to lose weight, it is important to…?", whereby the respondent could select one of the following options: "Perform extra physical activity, but give no special attention to diet", "Refrain from eating snacks between meals", "Eat two pieces of fruit and 200 grams of vegetables every day and refrain from eating bread and potatoes", or "Eat regularly and diversely, but not excessively, and exercise sufficiently" (correct answer).

On day 14 of the study, participants received an email referring them to the survey on self-management motivation. On day 28, participants received an email referring them to the closing online survey. It assessed self-management motivation, lifestyle knowledge, BMI, and a usability evaluation of the diary. The usability survey comprised questions about the contribution of the diary to maintaining a healthy lifestyle, ease of use, relevance, trust, and educational value. Answers were provided on a 5 point Likert scale: low, fully disagree; average, neutral; high, fully agree. Finally, the participants received a debriefing document.

To evaluate the influence of personal characteristics on attrition, we compared groups within the overall attrition data. Based on the description of attrition in RCTs of eHealth and the classification of dropouts of Davis and Addis[7], we defined four attrition stages in RCT of eHealth services for self-care. Based on the number of participation days and completion of surveys, we assigned the participants to one of the following attrition groups: (i) *First glimpser*: A participant matching the inclusion criteria does not return to the trial after the recruitment (i.e., after 1 day); (ii) *Early dropout*: The included participant samples the service for some days but drops out before providing longitudinal data (i.e., between 2 and 5 days); (iii) *Late dropout*: The participant takes part in the trial for a prolonged period, but quits before the end of the trial without completing the closing surveys (i.e., between 5-27 days); and (iv) *Maintainer*: The participant takes part in the entire trial and completes the closing survey; note that the person may or may not use the service for the full length of the trial but does participate in all the assessments (i.e., between 5-27 days + completing closing survey or 28 days).

Analysis
To evaluate the influence of the computer assistant on the self-management process, we performed a t-test for independent variables. To evaluate the influence of the computer assistant on the self-management outcomes, concerning lifestyle knowledge, motivation, and BMI differences across the four-week period, we performed a repeated measure ANOVA.

To evaluate the influence of personal characteristics on the discussed groups of attrition, we applied a Chi-square (χ^2) analysis. We evaluated the effects of personal characteristics on the number of days participants took part in the study. Here we applied a regression analysis (linear forward stepwise regression) with 10 predictors (i.e., age, gender, education level, initial BMI, computer experience, locus of control, vocabulary, initial lifestyle knowledge, motivation to maintain a diary, and motivation to perform self-care). Finally, we compared the attrition groups on personal characteristics using a χ^2 analysis.

The confidence limit was set at 0.05 in all statistical tests.

Results
Participants with the computer assistant completed their diary more often, $t(116)=3.04$, $p<0.05$, and over a longer range of days, $t(116)=1.98$, $p<0.05$, than participants without the assistant. Participants' self-reported motivation to complete the diary and motivation to perform self-care declined over the period of four weeks, $t(65)=4.75$, $p<0.001$, and $t(63)=1.91$, $p<0.05$, respectively. A Kruskal-Wallis ANOVA analysis was conducted due to the low number

of participants who completed the end survey. Participants with the computer assistant declined less than the participants without a computer assistant, H(1,32)=4.47, $p<0.05$, and H(1,32)=5.56, $p<0.05$, respectively.

People working with the diary lowered their BMI significantly. Moreover, people with the computer assistant decreased their BMI even more, F(1,28)=13.84, $p<0.001$. Participants scored higher on knowledge of maintaining healthy lifestyle at the end, than at the beginning of the study, F(1, 30)=50.81, $p<0.001$. There was no difference between participants' score with and without computer assistant. Finally, participants evaluated the diary's usability and participants with computer assistant appraised the diary as easier to use, than participants without a computer assistant, Z(34)=2.27, $p<0.05$.

At the end of the study, participants evaluated the diary's usability (i.e., ease of use, relevance, and trust). On a scale from 1 (low) through 5 (high), 35 participants rated its usability (*Table 2*). Overall, the online diary was rated above average on the three usability factors.

Despite these important findings, a steep decline was seen in the number of online diary users over the course of the study, instead of a gradual line (*Figure 2*). Throughout the study we logged the number of times a participant used the diary over the course of the 4 weeks. The Law of Attrition applied in this study: of the initially 191 registered people, 57 did not return after the first day and were not included in the study. Furthermore, 16 did not return after day 5, which we defined as the minimum number of days. A similar decline was evident for the number

Table 2. Evaluation of the usability of the diary at the 5 point Likert scale (1=low, 3=neutral, 5=high); n=35; SD=standard deviation

Usability aspect	Frequency/score, %					Score	
	1	2	3	4	5	Mean	SD
Ease of use	11	14	9	43	23	3.5	1.3
Relevance	6	0	31	34	29	3.8	1.1
Trust	8	14	29	26	23	3.4	1.2

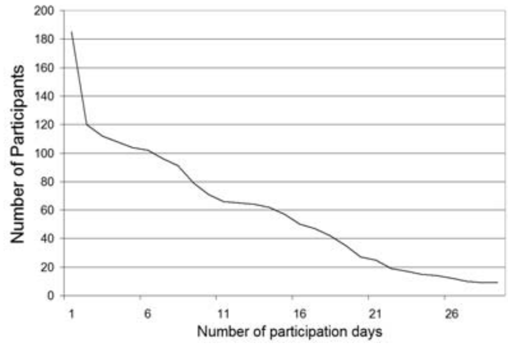

Figure 2. Declining number of participants/day in the study on the use of the online lifestyle diary with a personal computer assistant, from 191 on the first day to a mere 10 on day 28

of participants who completed the surveys during the study (*Table 1*), going from 118 to 50 to 35 at the end. As discussed in the introduction, this high dropout rate inspired analysis of the determinants of participants' attrition in eHealth studies.

The initial group consisted of 191 registered participants. As we logged the number of times a participant used the diary, we could assess how many days they participated in the study and when they dropped out. We assigned the 191 participants to the four categories of attrition: (i) First glimpser (1 day): 57 participants (30%); (ii) Early dropout (2-5 days): 16 participants (8%); (iii) Late dropout (5-27 days): 89 participants (47%); and (iv) Maintainer (5-27 days + completing closing survey or 28 days): 29 participants (15%).

When we compared the numbers in the different groups, it was notable that the largest groups were First glimpsers and Late dropouts. Participants either decided very early not to participate, or participated for a prolonged period, but not until the very end, $\chi^2(3)=66.22$, $p<0.001$. Understanding the personal characteristics that affect attrition of these groups in particular may be very beneficial for decreasing attrition in RCTs evaluating eHealth services.

The linear forward stepwise regression showed that Locus of Control, Vocabulary, and Motivation to perform Self-Care explained 19% (adjusted R^2) of the variance in attrition (i.e., the number of days between first and last day of diary use), F(3,181)=8,36, p.<0.001 (*Table 3*). The residual passed the normality check.

We divided the participants' scores for locus of control, vocabulary, and motivation to perform self-care into low (under median) and high (above median) and conducted Univariate Analysis of Variance. High scores on internal locus of control, F(1,183)=14.48, p<0.001), vocabulary, F(1,183)=5.15, p<0.05), and motivation to perform self-care, F(1,184)=3.12, p<0.05, were positively related to the number of days people participated in the study and vice versa. The other personal characteristics (i.e., age, gender, education level, initial BMI, computer experience, initial lifestyle knowledge, motivation to maintain a diary) did not explain variance in attrition in this study.

Participants with an external or internal locus of control and a low or high score for vocabulary and motivation to perform self-care were divided amongst the four attrition groups (*Figure 3*). For participants with an external locus of control, the First glimpsers (36%) and Late dropouts (43%) were proportionately over-represented whereas the Maintainers (9%) and Early dropouts (11%) were proportionately under-represented. For participants with an internal locus of control, the Late dropouts (53%) were proportionately over-represented, the First glimpsers (17%) and Early dropouts (6%) were proportionately under-represented, and Maintainers (23%) were moderately represented. In addition, First glimpsers more often had an external locus of control, $\chi^2(1)=8.65$, p=0.003, whereas Maintainers more often had an internal locus of control, $\chi^2(1)=4.17$, p=0.04.

Table 3. Regression analysis of the effect of personal characteristics on variance of number of days participating in the study; n=185

Parameter	**B**	**Standard error**	**ß**	**t**	**Significance**
(Constant)	-1.63	0.42	-	-3.86	0.001
Locus of control	0.02	0.00	0.31	4.60	0.001
Motivation for self-care	0.16	0.05	0.20	2.99	0.003
Vocabulary	0.04	0.01	0.20	2.90	0.004

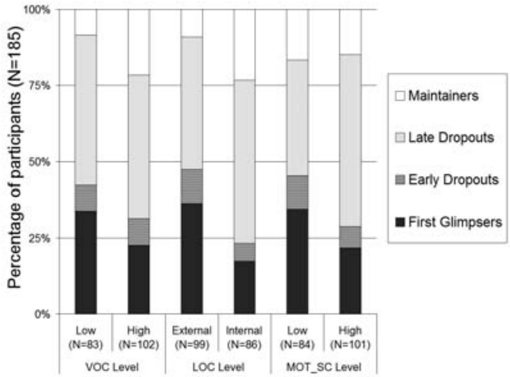

Figure 3. Distribution of low scores (Likert scale 1) and high scores (Likert scale 5) per attrition group for the contributing factors vocabulary (VOC), locus of control (LOC) and motivation to perform self-care (MOT-SC); n=185

For participants with a low score on vocabulary, First glimpsers (34%) and Late dropouts (49%) were proportionately over-represented whereas Early dropouts (8%) and Maintainers (8%) were proportionately under-represented. For participants with a high score on vocabulary, Late dropouts (47%) were proportionately over-represented and Early dropouts (9%) were proportionately under-represented; First glimpsers (23%) and Maintainers (22%) were both moderately represented. In addition, Maintainers scored higher on vocabulary, $\chi^2(1)=7.76$, p=0.005.

For participants with a low score on motivation to perform self-care, First glimpsers (35%) and Late dropouts (38%) were proportionately over-represented whereas Early dropouts (11%) and Maintainers (17%) were proportionately under-represented. For participants with a high score on motivation, Early dropouts (56%) were proportionately over-represented, Late dropouts (7%) and Maintainers (15%) were proportionately under-represented, and First glimpsers (22%) were moderately represented. In addition, Late dropouts scored higher on motivation, $\chi^2(1)=7.02$, p=0.008.

Discussion

To address the recurring phenomenon of high dropout rates in RCTs of eHealth services (i.e., the Law of Attrition)[2,6], we analyzed an RCT of an online lifestyle diary with a Personal Computer Assistant to determine the effects of personal characteristics on the stage in which people dropped out[18]. In line with earlier research[7], these four attrition stages, i.e., First glimpser, Early dropout, Late dropout, Maintainer, were related to the number of days people participated in the study. We included characteristics which are known to influence technology use and which tend to diversify as people grow older. The factors were age, gender, education level, initial BMI, computer experience, locus of control, vocabulary, initial lifestyle knowledge and motivation to maintain a diary and to perform self-care. Through this analysis, our goal was to establish determinants of attrition and to identify strategies to overcome this Law of Attrition barrier and, in turn, offer guidelines for research on and implementation of eHealth services for self-care.

Locus of control, vocabulary, and motivation

Locus of control, vocabulary, and motivation to perform self-care explained variance in the number of days people partook in the study. Moreover, when we differentiated the four stages of attrition, we found that these groups were related to low and high scores on locus of control, vocabulary, and motivation (*Figure 3*). With respect to locus of control, people with external locus of control, in general, tended to dropout earlier whereas people with an internal locus of control tended to stay in the study longer. Moreover, First glimpsers and Early dropouts more often had an external locus of control, whereas Maintainers more often had an internal locus of control.

With respect to vocabulary, people with a low score on vocabulary, in general, dropped out earlier, whereas people with a higher score stayed in the study longer. In addition, Maintainers scored higher on vocabulary. With respect to motivation to perform self-care, people with a low score on motivation, in general, dropped out earlier whereas people with a high score stayed in the study longer. Late dropouts also scored higher on motivation.

Overall, people who had an external locus of control and scored low on vocabulary and motivation were more likely to try-out the eHealth service for a couple of days, but drop out before providing longitudinal data. People with an internal locus of control and higher scores on vocabulary and motivation were more likely to use the service for a prolonged period and complete the closing survey, which enabled full evaluation of the eHealth service.

Study limitations

Although our findings contribute to the Law of Attrition discussion, the three determinants we established are likely not exhaustive. For example, we consciously included a small number of surveys because requesting too many surveys may be overwhelming and could lead to attrition by itself[27]. As observed in our study, only a marginal number of participants completed all the surveys. Additional measures of crystallized intelligence (e.g., general or domain knowledge) and fluid intelligence (e.g., problem solving ability) might also be related to dropout rates in eHealth studies. As previous research has shown a relationship between crystallized intelligence and technology use[11], further research should study the effect of these factors on the Law of Attrition.

Second, although we aimed for objective randomization to include people in our study, the lack of male participants leads to a bias in the analysis of gender related effects on variance in eHealth use. Although this is a recurring issue in research on eHealth[9], it is unclear whether it is representative for use of eHealth for self-care in non-research settings. Accordingly, the effect of gender and gender related determinants should be further discussed in relation to the Law of Attrition in eHealth research (e.g., are men less likely to partake voluntarily in studies) and the use of eHealth for self-care (e.g., are men less motivated to perform self-care with the use of eHealth).

And third, we focused on a sample with a wide age range (21-65) and a mean that was middle-aged (43). Perhaps surprisingly, age was not an additional predictor of attrition. Future efforts must investigate older ages to determine whether this pattern holds. Nevertheless, the variables we measured typically show age-related changes and are therefore likely to be predictive of attrition (perhaps even more so) for older participants.

Coping with attrition

The present findings suggest that when conducting an RCT of eHealth services, a strategy to cope with and possibly mitigate attrition is to acknowledge determinants of attrition and attempt to mitigate their effects on RCT studies and outcomes. A starting point is to include enough participants in the study to ensure that the number of people who are more likely to drop out are equally represented in both intervention and control group. In addition, the use of technology can enable automatic (thus without interfering with the double-blinded RCT set up) surveying of the determinants, assessing those who are more likely to drop out early, and allocating them equally to intervention and control group.

During the RCT, addressing the effects of the attrition determinants can be done in two ways. First, both the technical applications that guide people throughout the study (e.g., online recruiting tool, manual, surveys) and the eHealth service examined need to attend to the three determinants of attrition established in our study. Although this also applies to younger users, it certainly applies to older adults, who do not necessarily have lower score on characteristics, such as internal locus of control, cognitive abilities and motivation, but experience greater variance in them[29].

With regard to locus of control, developers should recognize that it is not everyone's opinion that the care of their health is (mainly) in their own hands. In the support of self-care through eHealth, Motivational Interview (MI), which focuses on enabling social functioning, discussing problems, and giving feedback in the form of advice and direction in an empathetic way, could help people with a stronger external locus of control[19]. Concerning vocabulary, it is essential to pay extra attention to readability. For example, manual information can be presented in small pieces and in a layperson's language. Besides making it more enjoyable to read, it makes it easier for the participants to understand the utility of the service and what is expected of them during the study (which can help prevent disappointment and thus dropping out)[29].

A possible alternative to efficacy trials such as RCTs, are effectiveness trial (i.e., studies of how much benefit actual patients gain from therapy). This study protocol is more flexible to accommodate attending to the varying personal characteristics that determine if a patient will use an eHealth service for self-care[7]. However, effectiveness trials cannot be conducted with random population samples and rely on retrospective observations, at the cost of data accuracy. Although a shift from efficacy to efficiency takes place in the health care domain, we need to find a balance between the costs and benefits of both approaches, when it concerns technical medical interventions.

Conclusion

In conclusion, future RCTs of eHealth services for self-care need to include measurements of personality factors (e.g., locus of control), cognitive abilities (e.g., vocabulary), and motivation to perform self-care, as they are important determinants for attrition. Also, researchers need to bear in mind that these factors increasingly vary from person to person, as they grow older. Moreover, applying the discussed strategies (i.e., distributing participants with determinants equally between groups, facilitating minimal impact of determinants on studied eHealth service, and reconsidering the application of effectiveness trials) can help to further establish an eHealth evidence base and increase the adoption of eHealth technology, for adults of all ages.

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