Lifelong learning with a digital math game: performance and basic experience differences across age

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Abstract. Gaming is acknowledged as a natural way of learning and established as a mainstream activity. Nevertheless, gaming performance and subjective game experience were hardly examined across adult age groups for which the game was not intended to. In contrast to serious games as specific tools against a natural, age-related decline in cognitive performance, we evaluated performance and subjective experiences of the established math learning game *Semideus* across three age groups from 19 to 79. Observed decline in performance in terms of processing speed were not exclusively predicted by age, but also by gaming frequency. Strongest age-related drops of processing speed were found for the middle-aged group aged 35 to 59 years. On the other hand, more knowledge-dependent performance measures like the amount of correctly solved problems remained comparably stable. According to subjective ratings, the middle-aged group experienced the game as less fluent and automatic compared to the younger and older groups. Additionally, the elderly group of participants reported fewer negative attitudes towards technology than both younger groups. We conclude that, albeit performance differences with respect to processing speed, subjective gaming experience stayed on an overall high positive level. This further encourages the use of games for learning across age.

Keywords: game-based learning, life-long learning, reliability, applicability, number-line estimation, user-experience, elderly

1 Introduction

While gaming is largely established as a mainstream activity among teenagers and (young) adults alike [e.g. 1], there is also a substantial share of gamers aged 50 and above. The ESA reports that with 21 % of gamers beyond the age 50 this age group shows the second highest percentage together with the age group of individuals 18 years and younger [2]. In the vein of Huizinga's 'Homo Ludens' [3], there seems to be no decline in the engagement in playful activities with age. This leads to the intriguing question why the attempt to exploit, for instance, the motivational potential of games for learning still focuses primarily on younger populations [e.g. 4]. Educational studies widely acknowledge that play is a natural way for children to learn [5]. Yet, there seems to be a traditional dichotomy between learning and playing [6]. Moreover, the gradual detachment of learning and playing with higher levels of the educational system [7] seems paradoxical [8]. In the current study, we try to apply a math game on fraction knowledge, usually played by primary and/or secondary school students, to age groups from 19 to 79 in order to explore differences of game-related performance as well as subjective experiences with respect to the game-based learning environment.

(Serious) Games and their applications for the adult and elderly population. Serious games for rehabilitation purposes are becoming increasingly popular [9] and can be distinguished in three types: physical, cognitive, and social as reported in the review of Ngyuen and colleagues [10]. While games aiming at physical and cognitive effects make up most of the studied effects, about 75% of studies also found a positive impact on well-being in the elderly [10]. However, there are restrictions in the interpretation of these results. Most of the reviewed games were utilized to compensate impairments and disabilities on the physical or cognitive level (e.g., memory, attention, problem solving, etc.), acquired through diseases or injury, and to overcome repetitive characteristics of therapy and training processes [11]. Besides actual clinical conditions, there is a natural association between aging and a decline in cognition and perception as well as an increase in physical impairments which should be considered in the design of games [e.g. 12, 13]. So far, most articles examined the impact of digital games on well-being, brain plasticity or decreasing cognitive abilities in (children and) seniors. However, healthy adult populations were found to benefit from game-based trainings as tools to enhance cognitive and emotional skills as well [14]. Importantly, a recent book takes a perspective on senior gamers and games for the elderly in general and goes beyond aspects of compensation of age-related or incidence-related declines. It explicitly avoids the view of reducing "…older players to a stereotype or design for them without talking and testing game designs with them." [15] but includes knowledge and experience of older generations by establishing a framework for game-based lifelong learning [6] or intergenerational game-design workshops [16] to promote, for instance, intergenerational learning and exchange.

Gaming through the lifespan: The *gerontoludic manifesto* [17] suggests (amongst others) that gaming research and design should focus on heterogeneity but not on stereotyping, because older gamers vary considerably in terms of preferences, experiences or health status. Not only for the adult, but also for the (healthy) elderly population, this raises the question whether commonly used games in the context of learning or even entertainment maintain their applicability with respect to their main qualities, they are usually evaluated on. While mobile applications were already successful in, for instance, assessing cognitive functions across the lifespan [e.g. 18], to our knowledge only one study examined the same gaming environment on heterogeneous age samples. The authors assessed motor development with a Kinect sensor across the lifespan embedded in a serious game for rehabilitation [19]. The study replicated that cognitive performance across the lifespan first increases and then decreases again – a quadratic trend known from neuropsychological evidence on maturation [20] and aging [21] suggesting a climax of cognitive performance in terms of processing speed in the mid 30's.

To advance and extend this knowledge to the cognitive domain in terms of acceptance and applicability of serious games, we used a tablet-based math game that is usually played by and designed for high school aged children. According to previous research, the "acceptance of serious games is independent of gender, technical expertise, gaming habits, and only weakly influenced by age. Determinants of acceptance are perceived fun and the feeling that the users can make playing the game a habit."[22]. This means that subjective experiences should have a high impact on the acceptance of serious games. In contrast, performance in the game should mostly be influenced by age and previous gaming experience [22]. For the current purpose, we followed a similar distinction, separately evaluating the game with respect to the domains *Cognition* and (subjective) *Player Experiences/Attitudes.*

Cognition. The present game aims at assessing and training fraction understanding. Generally, deficits in numerical competencies can have critical drawbacks on an individual as well as societal level [23]. The game comprises two tasks, of which the first one, *number-line estimation*, requires the player to navigate an avatar along a horizontal number-line to accurately indicate the correct location of a target fraction (e.g. where goes 4/7 on a number line from 0-1?). This type of task is commonly used for training number magnitude understanding [e.g. 24] and performance in this task is associated with mathematical achievement [25]. In the second task, *magnitude comparison*, the magnitudes of two fractions need to be compared. Both tasks can be evaluated in terms of speed (how much time to solve a comparison/number-line estimation) and error rate (how many correct items per session). The number-line estimation task also captured accuracy (how close was the indicated solution to the correct location).

Age related cognitive declines are most significantly found in components of fluid cognition [26] such as processing speed [27], whereas the crystallized part of cognition, this means knowledge and experience, is comparably stable, rarely starting to decline until the age of 65 [26]. While in-game performance measure such as speed can clearly be attributed to the former part of cognition, error rate/accuracy should be more (fraction) knowledge-dependent and therefore part of the latter domain. We generally expected an overall age-related decline in performance. However, this should be true for measures associated with speed, but not necessarily for others (e.g. accuracy). We further hypothesise that in-game performance metrics might be influenced by participants' prior tablet use and their gaming frequency.

Player Experiences/Attitudes. Additionally, we were interested in whether and how players across different age groups might perceive and experience the game differently. Therefore, we assessed participants' experienced flow, a widely used measure in game-based learning [28]. We further captured other aspects of user experience such as attractiveness, pragmatic quality (e.g. handling) and hedonic quality (e.g. novelty) of the game, that are often investigated when evaluating software [29, see e.g. 30]. Finally, we also try to shed light on the question whether there is an age-related change in general affinity and attitude towards technology [31, 32], which in the context of serious games, has not been evaluated so far.

2 Methods

The game took about 10-15 minutes, involved both number line estimations and magnitude comparisons, and was completed by 3 different age groups (see section 2.1 below). For both tasks we compared performance across 3 age groups. Data presented in this paper is preliminary and part of a larger ongoing project including other measures such as basic intelligence scales and assessments of basic math competencies, which are not relevant for the current study.

2.1 Participants

78 adults from three age groups participated in the current study: (i) 33 participants below 35 years of age (*M* = 25.15 years; *SD* = 3.76 years; 25 females), (ii) 21 participants between 35 to 59 years of age (*M* = 46.05 years; *SD* = 6.83 years; 25 females) and (iii) 24 participants aged 60 years and above (*M* = 66.04 years; *SD* = 4.35 years; 11 females). Participants were recruited via online and newspaper advertisements. The study was approved by the local ethics committee.

2.2 Measurements

The first and main part of the current study was the assessment with the learning game *Semideus*. As mentioned above, the game consisted of two tasks, *number-line estimation* and *magnitude comparison*. In the former, participants are asked to indicate the spatial position of a target number/fraction (e.g. 5/8) along a number-line with fixed ends (e.g. 0 and 1; see Figure 1). This task is complemented by the comparison task, in which participants had to put two fractions, represented by two piled blocks that displayed two different fractions, in ascending order with regard to the numerical magnitudes depicted on them (e.g., which is larger 4/7 or 1/2). The game was played on an Apple iPad. The main mechanics of the game required controlling the avatar walking along the number-line by tilting the Tablet. All other operations such as confirming to be on the right position on the number line are realized via button presses on top-left or top-right positions on the touchscreen. The game-session involved an onboarding phase and the actual assessment phase. The former was assisted by the experimenter and

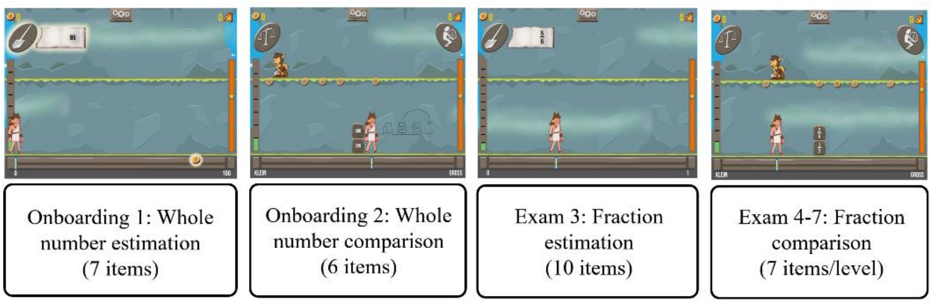

Figure 1. Screenshots of “Semideus” showing the level structure.

aimed at familiarizing players with controls and game mechanics. Hence, whole numbers instead of fractions were used in this phase. The latter was played without assistance and only these data were analysed in the current study (for further details see also [33], Figure 1 and https://youtu.be/rhl88VvGCvI). Therefore, assessments regarding the *Cognition* domain took place in-game. The time to solve each item (speed), the number of correct items (error rate), and for number line estimation the accuracy of correct estimations were used (note that an estimation was considered correct when not more than 8% off the correct location).

The second part of the current study comprised questionnaires regarding the (subjective) *experiences* domain. To measure subjective experiences with the game and attitudes towards technology we employed the Flow-Scale (FKS [34], subscales: automaticity, absorption), the User Experience Questionnaire (UEQ [29], subscales: attractiveness, pragmatic quality, hedonic quality), and a questionnaire regarding general affinity for technology (Fragebogen zur Technikaffinität (TA-EG) [35], negative/positive attitude toward technology).

Finally, gaming frequency (never = 5 to daily = 1, scale was recoded for analysis) and tablet use (never = 1 to daily = 7) was assessed on a Likert scale.

2.3 Procedure

Before playing the game on the tablet participants received written instruction on the handling and the tasks within the game. Next, participants started the onboarding phase which included 7 number-line estimation tasks and 6 magnitude comparison tasks, both with whole numbers instead of fractions to lower the initial hurdle. This phase contained one level with 10 estimation items and three comparison levels with 7 items each. Game-play was immediately followed by the utilized questionnaires.

3 Results

Cognition. We analyzed group differences using regression models, comparing each age group against its younger one using gaming frequency and tablet use as additional predictors. Performance variables were divided into speed, error, and accuracy measures for both tasks with accuracy only evaluated for number line estimation. Hence, we analyzed a total of five models. The only significant model in our analysis was the one on speed in the comparison task. It explained 27.4 % of variance [*adj.* R^2=.274, $F(4,73)=8.272$, $p<.001$][1]. Group 2 (35-59 years) showed a significant increase in time needed to solve the comparison task (β=0.256, $p<.05$) in comparison to group 1 (19-34 years), but this was not present for group 3 (60 years and above) when compared to group 2 (β=0.181, p=.13). Additionally, higher gaming frequency significantly predicted higher speed in the comparison task (β = -0.266, p<.05). Tablet use did not

[1]Results did not change substantially when age was used as continuous variable: [*adj.* R^2=.309, $F(3,73)=12.36$, $p<.001$]

account for unique parts of the variance (β = -0.097, p<.05). The model on number of errors for magnitude comparison was not significant [*adj.* R^2=.049, F(4,73)=1.998, p=.104].

No significant models were identified for speed [*adj.* R^2=.053, F(4,73)=2.076, p<.1][2], number of errors [*adj.* R^2<.01, F(4,73)=0.607, p=.65], and accuracy for number line estimation tasks [*adj.* R^2<.01, F(4,73)=1.04, p=.39].

Player Experiences/Attitudes. We used separate multivariate analyses of variance (MANOVAs) for each questionnaire to examine differences between age groups. For the flow-scale, the analysis revealed marginally significant group differences [F(4,148)=2.0695, p=.088, η^2 =.053; see Figure 2]. Univariate post-hoc t-tests showed that group 2 (M=29.380) felt the game experience to be more fluent or automatic, respectively (p<.05). No differences were found for absorption.

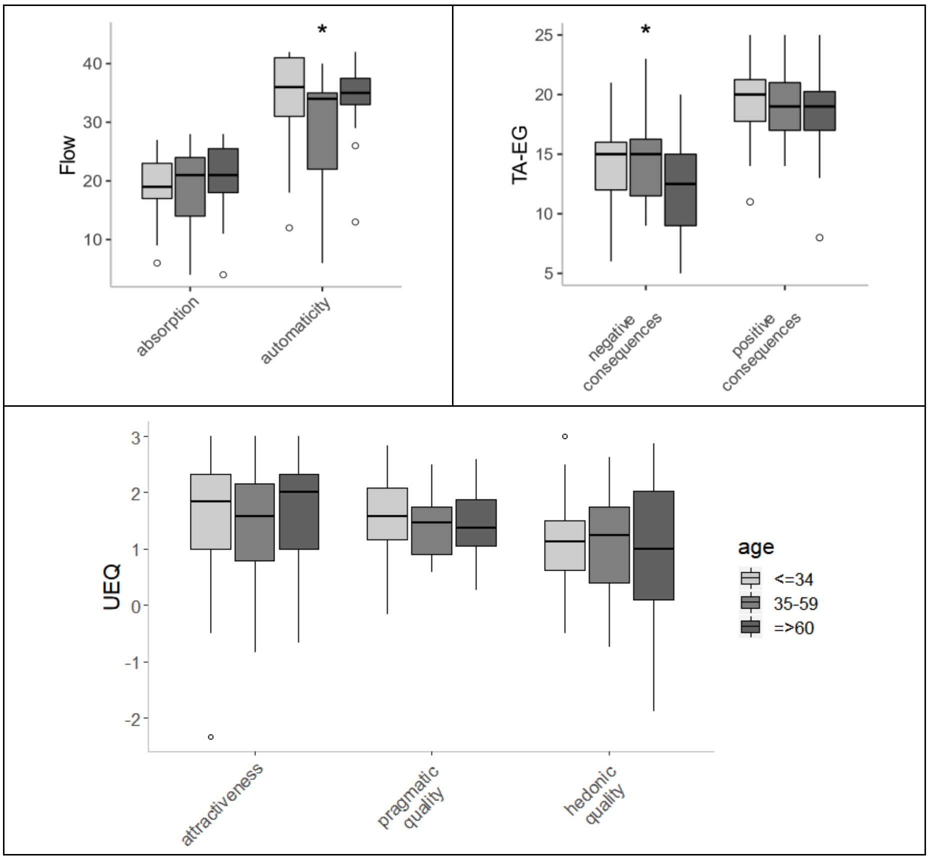

Figure 2: Top left: Flow scale. Top-right: Affinity for technology scales. Bottom: User Experience Questionnaire – UEQ. The bold horizontal line represents the median and the lower and upper hinges correspond to the first and third quartiles. Upper and lower whiskers extend from the hinge no further than 1.5 * inter-quartile range. Asteriscs indicate significant comparisons.

[2] Results did not change substantially when age was used as continuous variable: [*adj.* R^2=.016, F(3,73)=1.41, p=.246]

Affinity for technology scales showed a significant effect for age groups [(F(4,146)=2.070, p=.019, η^2 =.077; see Figure 2]. Univariate post-hoc t-tests indicated that means for both group 1 (M=14.515) and group 2 (M=14.650) were significantly higher than for group 3 (M=12.126, both p<.05). That is, groups 1 and 2 anticipated more negative consequences for society from technology use than the elderly group.

Finally, no significant group effect was revealed with respect to the user experience questionnaire [F(12,140)=1.2141, p=.279, η^2 =.094; see Figure 2].

4 Discussion & Conclusion

In the current study, we focussed on two domains of game-based learning across age, *cognitive* factors such as performance and subjective *experiences* as a user/player. By addressing these aspects across age, we gained new insights into the applicability and usability of an existing, evaluated, and well documented game-based learning environment for age groups other than it was originally intended and designed for.

With respect to the cognitive domain, we hardly found age-related changes of performance. Findings related to speed were largely congruent with evidence on general cognitive ageing in terms of an age-related decline in speeded performance [27]. However, strong speed-related effects of age were only present in the comparison task. Moreover, gaming frequency was another significant predictor of speed differences alongside age. That is, young players between 19 and 34 years of age responded to faster than participants aged 35-59. Interestingly, a similar effect was not found for number-line estimation. However, our predictors or model, respectively, did not explain number line estimation data significantly so that it is likely that there is/are an unknown factor/s influencing speed in number-line estimation. For the comparison task, we may assume that, on the one hand, processing speed reflects overall age-related performance decline, but, on the other hand, handling differences between tasks might have affected results as well. These might arose because the comparison task required players to perform a more complex combination of tilting and pressing two additional buttons on the tablet to successfully solve an item as compared to the number line estimation task. In magnitude comparison trials players had to pick up the stones/fractions (button press) and place them (tilting) according to their numerical magnitude. This might have placed additional obstacles for older participants than the number line estimation task, where only tilting (i.e., navigating the avatar to the correct location) and one button press (i.e., confirming the location) was required. However, this alternative interpretation was not substantiated by our results as player's tablet use did not significantly predict speed in magnitude comparison (or number line estimation). Moreover, pragmatic quality (i.e. handling) of the game was rated similar across age groups.

Our analysis showed that the most significant performance drop as regards speed occurred in the group aged between 35 to 59 and not within the age group above 60 years. Finally, we were not able to explain any differences in error rates or accuracy across age. This might be due to the fact that the ability to just correctly or accurately solve the tasks of the game is primarily knowledge-based and part of the crystallized part of cognition, which is rather stable across age [26].

Differences in (subjective) experiences across age groups were found for flow experience and affinity for technology. Participants aged between 35 and 59 experienced gaming as a less automatized process (e.g. “having more trouble to concentrate”) compared to both other age groups. Furthermore, together with the youngest group of participants they seemed to anticipate more negative influences of technology use/digitalization on society than the group aged 60 and above. Seemingly consistent with above reported results on performance, a more negative attitude towards technology and less experience of automaticity during gameplay may accompany the performance decline in the middle-aged group. Most prominently, we did not find differences across age in terms of perceived quality of the game or its attractiveness to the individual participant.

Accordingly, we found no signs of a decline of the perceived entertaining nature of the game nor its pragmatic quality (including its controllability and handling). Generally, players across all age groups rated the game equally positive.

From a game-design perspective, we may conclude that games using, for instance, scaffolded feedback and high scores that depend on player’s in-game performance should adapt these features to age appropriate norms. Particularly with respect to speed related feedback elements, there might be the chance that, for example, inappropriate or even continuously lowered rewards because of lower speeded play might lead to undesirable effects like demotivation and frustration of elderly player.

Future studies should continue to investigate factors influencing age-related performance differences in digital games. Our analyses revealed that age, gaming frequency, and tablet use do not cover the entire variance at least in the non-speed-related performance measures of our study. First, educational and professional background may be potentially relevant variables contributing to differences not only within but also across age groups. Second, education/profession and gaming experience should be assessed and examined in more detail. For instance, gaming experience may qualitatively vary over the lifespan, for instance, different game genres played or devices used by different age groups [e.g. 2, 18]. Literature, for instance, suggests that video game experience is differentially associated with cognitive markers like memory and attention in older adults compared to the younger population [18]. Additionally, more attention should be drawn on the details of the relationship between experiential and performance dimension in game-based learning environments across age.

In conclusion, we did only find age-related declines in in-game performance measures reflecting processing speed. However, the observed relationship was never exclusively due to age but also influenced by gaming frequency. A significant drop in speed seemed to take place within the age range of 35 to 59 rather in the range above 60. Although designed for a different target group (i.e., elementary and secondary school students), we did not find conclusive evidence that individuals of different higher ages perceived or experienced the game differently in general. Only the middle-aged group experienced playing the game as a less “fluid” or automatic process, whereas elderly participants and younger adults rated the game comparably positive. In sum, alongside literature-consistent performance differences, experiences with the math-game originally designed for a younger target group did not seem not to vary significantly across the ages from 19 to 79.

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