Game over or continue? How gamification can improve completion rate in adaptive learning

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Game over or continue? How gamification can improve completion rate in adaptive learning

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Abstract

Despite the potential for personalized learning, e-learning courses often suffer from low completion rates. In order to address this issue, we propose and empirically test a theoretical mechanism that examines how gamification can enhance the completion rate in adaptive learning courses by promoting a more positive behavioral response and attitude among students. To identify causal effects, we employ a quasi-experimental design with a time-discontinuity in treatment attribution. Our study involves a sample of 6592 adults who participated in a Belgian financial education platform. The effect sizes were estimated using non-parametric survival analysis. Our findings indicate that gamification led to a 5.7% increase in the number of questions answered and a 1.6 percentage point rise in the completion rate. These effects were particularly pronounced among younger individuals, single adults, and in relation to socioeconomic status questions used in the personalization survey. However, gamification did not significantly impact the completion rate for decision-making questions. By demonstrating that gamification serves as a causal mechanism for enhancing completion rates in adaptive learning courses, our study contributes to the underlying e-learning theory. Specifically, we highlight the role of psychological factors, such as improved behavior and attitude, which are particularly relevant during personalization surveys.

Keywords Adaptive learning · Completion rate · Financial education · Survival analysis · Decision-making

1 Introduction

The digital necessity during the Covid-19 pandemic has illustrated that the shift to online learning and computer-based instruction in education is feasible, and even

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preferred in many cases (Camargo et al., 2020). As a major advantage, online learning is extremely cost-effective in terms of marginal costs to new students, which might help decrease the high cost of post-secondary school education (Nguyen, 2015). Adaptive learning[1] is seen as the personalization of learning and it is made possible by methods such as implementing intelligent learning systems and integrating learners' preference, which can be fundamental to improve students' learning outcomes in terms of affection, cognition, skills and behaviour (Brusilovsky et al., 1998; Graf & Kinshuk, 2006; Chang et al., 2009; Xie et al., 2019). Among others, adaptive learning was shown to improve students' engagement, acceptance and overall experience of learning systems (Gamrat et al., 2014; Tsay et al., 2018). On the other hand, in order to yield personalization, pre-test surveys with preferences and socioeconomic questions are usually needed, which are often long and time-consuming (Ocepek et al., 2013), in turn, negatively affecting persistence and completion rates (Janelli & Lipnevich, 2021). Although automatic preference systems might be an alternative, there are issues with their reliability (Akbulut & Cardak, 2012).

The objective of this paper is to evaluate the effects of gamification to the completion rate in computer-based online adaptive learning tools. Our paper contributes to the literature by proposing and empirically testing a theoretical mechanism on how gamification, in addition to affecting learning outcomes and satisfaction, can result in better behavioural responses that increase the completion rate in adaptive learning settings. We examine this in the context of financial advice material to adults. As argued by Kuo et al. (2021), it is highly relevant to investigate the psychological mechanism of pedagogical advancements in e-learning, namely gamification and other interacting features. In a systematic review of the MOOC literature, Rasheed et al. (2019) show that completion rate was the most frequently addressed topic. By using machine learning methods, Despujol et al. (2022) show that terms related to completion rate (e.g. drop-out, retention and course completion rates) are one of the most interesting cluster-topics to be considered for new research, while Schöbel et al. (2021) in their cluster-analysis show that there is still much more to explore on the use of gamification to construct good adaptive designs. Adaptive learning itself can have better completion rate than traditional learning methods (Fischman, 2011), but still, more investigation is needed, especially on the benefits of gamification to completion rate.

Although the effect of gamification to completion-rate was evaluated in online learning, surveys, and medical cognitive experiments (Pirker et al., 2015; Keusch & Zhang, 2017; Lumsden et al., 2017), there is still a lack of evidence of its use in adaptive learning. Mecca et al. (2021) and Polito and Temperini (2021) test the benefits of systems that include game elements to improve learning outcomes and completion rate for coding, while Hubalovsky et al. (2019) investigate the effectiveness of gamification and adaptive learning to primary school students learning about mathematics, languages and science, showing promising results. Still, to the best of our knowledge, no other papers in the literature focus on the benefits of gamification to the completion-rate in financial education applications, especially in adaptive learning. The present

[1] Also know as personalized learning.

paper differs from the latter ones in the application (i.e. coding in higher education versus financial education among adults) and the existence of well identified control groups to properly infer causal effects, which we address with our quasi-experimental approach.[2] Murillo-Zamorano et al. (2021) show the benefit of gamification in active learning to acquire skills such as the ability to work in groups, the ability to listen to others' opinions, and self-learning skills. However, their paper does not focus on the effects on completion rate. Blau et al. (2020) argue that self-regulatory skills, such as the skill to create an environment that makes it easier to complete a task, are a fundamental aspect to promote digital literacy and increase successful outcomes in e-learning. We argue that gamification can be one element that may improve such environment, which makes the learning process more enjoyable with a higher chance of being completed. As such, we investigate if the use of gamification can increase the completion rate in an adaptive learning environment.

In order to test the hypothesis that gamification can increase completion rates in online adaptive learning, we use a financial decision-making experiment based on adaptive learning simulation tools of a Belgian platform to help consumers with their decisions over disability insurance and pensions. This adaptive learning tool was aimed to improve the knowledge of Belgian adults about financial products available that could help their personal situation, and help them with future financial decisions.

In the tool, we have used a quasi-experimental approach with time-discontinuity to assign the gamification intervention. From a methodological perspective, to evaluate the effect of gamification we used survival analysis techniques such as the Kaplan and Meier (1958) estimates, the Cox (1972) Proportional Hazards Model and the Restricted Mean Survival Time model (Royston & Parmar, 2013). In addition to the time-discontinuous attribution to the control or the gamification treatment conditions, coarsened exact matching (Iacus et al., 2012) was used as identification strategy to improve the causal claims of our results. Due to the absence of self-selection in the discontinuity and the matching procedure, we claim causality of the estimated effects.

The results of the paper suggest that gamification has a significant effect to increase both the completion rate in the adaptive learning tool and the total number of questions answered. This effect was shown to have heterogeneity, being stronger for singles and younger people. The adaptive learning tool length also played a role, with longer courses having a smaller effect. Besides, the type of question also influenced the effectiveness of the gamification, with actual decision-making answers showing no significant effect, but during socioeconomic status questions (used to provide personalization) the effects were positive.

The next sections of the paper are divided as follows. Section 2 presents the literature review, followed by the methods section. Next, the results are presented in Section 3. In Section 4 we present the discussion of the paper. A final section provides the conclusion with limitations and future research.

[2] In a similar application to code learning, Rodrigues et al. (2022) address the identification of causal effects, but still focus on the learning outcomes and its effects across time.

2 Literature review-The challenges of gamification, online learning, and adaptive learning

A recurrent hypothesis is that gamification can play a role to improve completion rates, while improving behavioural efficiency and overall participant experience.[3] Gamification research has experienced a strong growth, emerging as a particular sub-field in the education and e-learning literature (Dichev & Dicheva, 2017; Dicheva et al., 2015). Gamification can be seen as "the selective incorporation of game elements into an interactive system without a fully-fledged game as the end product" (Seaborn & Fels, 2015), such as the inclusion of systems that can enhance motivation and engagement (Ghaban & Hendley, 2019; Simões et al., 2013). This use of game elements has a wide variety of applications, for instance in online learning, with the education literature already having ventured in its effects. One example is observed in the 'theory of gamified learning' (Landers, 2014; Sanchez et al., 2020), in which game elements could affect behaviour and attitudes, influencing learning outcomes. The effects of gamification have been investigated in the case of online evaluations and surveys. Gamification in surveys[4] often involve more visual elements; longer question wording; different response formats (e.g., drag and drop); and additional tasks, such as games between questions (Keusch & Zhang, 2017; Zainuddin et al., 2020). Recent evidence demonstrated that gamified courses resulted in higher student motivation, engagement and completion rates compared to traditional courses, with increased engagement being crucial for sustaining student interest and promoting continuous learning (Domínguez et al., 2013; Khaldi et al., 2023).

The general consensus in the literature is that gamification tends to improve psychological factors (e.g. fun, interest, satisfaction) but that it has mixed results on behavioural outcomes.[5] Gamification can increase interest and engagement in an e-learning environment , but these gains may decrease with time (Bai et al., 2022). They also show that gamification can (to a certain extent) improve behavioural outcomes: the inclusion of fantasy elements in gamification settings can improve both learning outcomes and interaction. Ogunyemi et al. (2022) and Hamari (2017) cite gamified elements, such as digital badges, as important indicators to increase engagement is MOOCs and other online environments. The recent literature shows that students' active engagement is encouraged with gamification due to higher motivation in both in-class and out-of-class activities (Huang & Hew, 2021; Jia et al., 2023; Sailer & Sailer, 2021; Quintas et al., 2020).

[3] Jonker et al. (2019) argued that the design of an evaluation experiment can be seen as a trade-off between statistical efficiency (e.g. more informative and quality choices) and behavioural efficiency (e.g. lower task complexity, drop-out, fatigue, and use of heuristics).

[4] Not only game elements can be beneficial to learning, but even the actual creating process of a game can be used as learning tool in the context of student centred learning (Marnewick & Chetty, 2021).

[5] This is the case of the online surveys literature, in which we still do not find a consistent directional effect of gamification to behavioural outcomes (e.g. drop-out rates and consistency of responses), such that the setting and specific details seem to matter (Keusch & Zhang, 2017; Warnock & Gantz, 2017; Guin et al., 2012).

Despite its benefits, there are valid concerns that gamification might divert attention from essential educational material. Critics argue that the emphasis on game elements, such as points and rewards, can overshadow the learning objectives and encourage superficial engagement. A study by Hanus and Fox (2015) found that while gamification initially increased student motivation, it also led to decreased intrinsic motivation over time as students focused more on earning rewards than mastering the content. Domínguez et al. (2013) show that despite students following gamified courses had better scores in practical assignments and in the final general score, they tended to perform poorly on written assignments and participate less on class activities,.This highlights the importance of carefully designing gamified activities to ensure they align with educational goals and promote meaningful learning.

Despite the advantages of both online learning and gamification, we acknowledge that a considerable inequality may exist regarding the potential number of impacted individuals due to the digital divide. We can understand the digital divide as the gap between individuals who have access to modern information and communication technology and those who do not, with Warschauer (2004) showing that the inability to effectively use these technologies for meaningful purposes also contributes to a wider digital divide, disproportionately affecting low-income students more. As noted by Deterding et al. (2011), the success of gamification in education is heavily dependent on students' ability to interact with and navigate digital platforms. Besides the matter of cost and ability to operate the technology, some individuals may be unable to have access to online platform due to living in remote areas without internet access, with the use of 'offline' e-learning replacement, such as through portable e-learning environments or through the use of television and radio broadcast (Hillier, 2020).

The global Covid-19 crisis brought the urgent need for fast worldwide solutions to help students with online learning opportunities, even in cases with a considerable digital divide, as the comparison among rural and urban students (Zhao et al., 2022). Tumwesige (2020) note the difficulty to reach students without internet access in Uganda during the pandemic, and that the online-learning initiatives greatly prioritized students which already had access to e-learning environments due to the digital divide. In the case of Bangladesh (Badiuzzaman et al., 2021), the main bottleneck for most students was not the access to the technologies and learning platforms, but the speed and reliability of the internet signal. For students with sufficient access to the technology and internet access, the use of synchronous e-learning methods (e.g. through platforms such as Zoom, Google Meet, and Microsoft Teams) appeared as satisfactory methods to help students missing face-to-face lessons (Jacques et al., 2021).

Additionally to the digital divide challenge, it is also important to acknowledge the costs behind online learning and gamification. Although online learning has the potential to decrease the cost to provide education for the additional student once the systems are already in place (Hjeltnes et al., 2005), the costs to both provide (i.e. for educational institutions) and receive (i.e. for potential students) this type of education appears as barriers of entry to adapt this technology (Bell & Federman, 2013). As noted by Bartley et al. (2004), online learning has the cost-advantage to optimize the infrastructure costs once the number of students is considerably increased, nonetheless, costs such as the purchase of digital equipment such as computers, video cameras, projectors, construction of IT rooms, service costs from dedicated IT support teams, training costs, and development cost of software and course in online format should be considered. For the case of specific case of gamification, besides the additional cost to develop and integrate the software or course using gamified elements, depending on the amount of game elements additional pieces of hardware may need to be purchased, as joysticks, video game consoles, and virtual reality headsets (Herzig et al., 2015; Tayal et al., 2022). Finally, when gamification courses use incentives, the cost of prizes should also be taken into account (O'Donovan et al., 2013). Still, recent applications show the appearance of close to zero-cost development platforms for gamification courses using open software solutions (Maican et al., 2016). As for the example case during the Covid 19 pandemic, the costs to develop, implement and use these technologies appear as barriers of entry to certain course creators (e.g. in low income countries and educational institutions) and to certain users (e.g. low income students), as discussed in O'Doherty et al. (2018) and Jaggars (2011).

Regarding adaptive learning, pre-test surveys can really appear as a double-edged sword. Such surveys with questions about preferences, knowledge, interest and socioeconomic are usually a necessity, with often negative effects to persistence and completion rates due to their length and time consumption (Janelli & Lipnevich, 2021; Ocepek et al., 2013). Although they designed to assess students' information and tailor the learning experience accordingly, they can demotivate students, particularly those who struggle with test anxiety or have low self-confidence by providing potentially difficult questions in the beginning of the learning experience (Liu et al., 2017). Still, the special focus on mental health, anxiety and emotions as elements during the adaptive learning process can become an asset to improve learning, professional abilities attainment, and improve retention rate, as this case for the training of new graduate nurses (Chen et al., 2021). Another possibility as a remedy, is the use of automatic preference systems that may reduce or eliminate the need for pre-test surveys to deliver the personalization of adaptive learning, but their reliability is still sub-par and may fail to provide the necessary personalization (Akbulut & Cardak, 2012).

3 Method

3.1 Theoretical research model and procedure

Landers (2014) and Sanchez et al. (2020) developed the 'theory of gamified learning', which consists on the use of game-like attributes with the objective to improve learning behaviours or attitudes outside the context of a game. A central aspect is that game characteristics (alongside the educational material) could influence behaviour or attitude, which would have a mediator effect to impact learning outcomes. Moreover, the extent of behaviour and attitudes could serve as mediators to the direct effect of educational material (i.e. instructional content) to learning outcomes. Even though the theory brought good foundations for the effects of gamification in the learning outcomes for e-learning, it did not focus on particularities of adaptive learning, nor on the effects of gamification to completion rate.

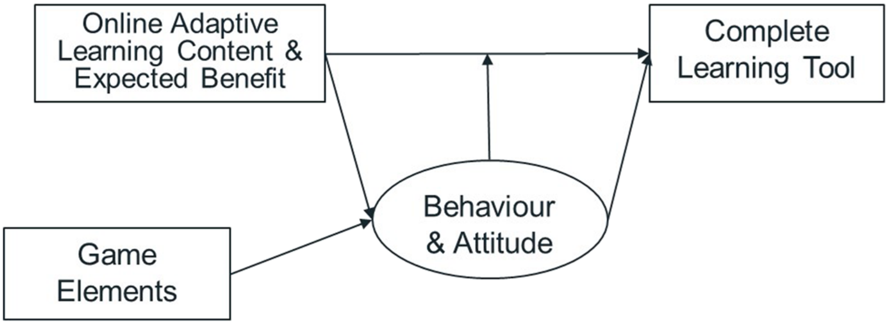

Fig. 1 Causal mechanism of gamification and decision to complete an online adaptive learning tool

We hypothesize that the theory of gamified learning can be applied to the context of online adaptive learning and to improve completion rates. Although any form of education has as primary desired outcome the attainment of learning outcomes, it is particularly interesting for online learning that the highest possible number of students can benefit from such outcomes. In Fig. 1, we present the causal framework visually. Here we modify the original framework in two ways. First, by changing the instructional content of a course to the online adaptive learning content and expected benefits of participation. Second, we alter the learning outcomes to the decision of completing the learning tool until the end (i.e. not dropping out). Squares represent observed variables and circles represent latent variables that are at least partially unobserved.

In our modified gamified learning framework, the content and expected benefit of the online adaptive learning tool can have a direct effect on the participation of a participant in the tool (e.g. the content or expected benefits can be attractive enough which can motivate the decision to complete), but it can also influence the behaviour and attitude of the participant, incurring in a mediation to affect the completion rate (e.g. content can make participant increase or decrease cognitive effort to complete the tool). As such, the behaviour and attitude of participants have also a direct effect to the drop-out rate (e.g. intrinsic motivation or abilities can affect the decision to continue the learning tool until the end). Besides, we note that behaviour and attitude can also have a moderating effect on the causal link between the adaptive online learning content/expected benefit and completion rate, since, for instance, the participant's cognitive effort or intrinsic motivation may let the tool to be more or less attractive.

In this paper, we examine if gamification is able to affect participants' behaviour and attitude, which can lead to a higher 'survival rate' in the tool. We make the hypothesis that gamification could increase motivation and engagement[6] of a participant in completing an adaptive online learning tool, which would lead to a greater completion rate. Considering that most of the intrinsic attitudes and behaviours of participants are unobserved (especially in online learning settings), we analyse this causal link by comparing completion rates of the treatment arms with and without gamification.

[6] Observed in the case of the effect of gamification to learning outcomes and motivation (Wilson et al., 2009).

3.2 Research context and sample

The experimental setting consists of two distinct online adaptive learning tools in the format of simulations to help consumers choosing for insurance disability and complementary pension products. To allow for adaptive learning possibilities, the learning tool includes a series of informative questions. The pension simulation had 22 questions, with questions 1 up to 20 being a personalization survey on socioeconomic status questions. The last part consisted of two decision-making questions about the participants' preference among personalized pension product best suitable for their needs, depending on the person's characteristics filled in the initial survey. Conversely, the insurance simulation had 15 questions, with the first 13 questions dealing with socioeconomic status questions and the remaining last two questions dealing with decision-making for insurance products. In Fig. 2 we show an overview of the types of question answered in each simulation.

Our design consists on a gamification intervention, to test if game-like elements were able to increase the completion rate.[7] The intervention attribution was based on a time discontinuity. The adaptive learning simulation tools were answered between 19th September 2020 and 18th December 2020. The participants that followed one of the simulations before December 4th did the experiment before the inclusion of gamification (i.e. with no gamified elements). Participants that followed the experiment starting on December 4th (or later), answered the same questions of the simulation, but in a setting with the inclusion of a gamification intervention. The time horizon of each sub-sample was an experimental design choice in order to have a similar amount of participants before and after the change in the experiment took place (i.e. the inclusion of gamified elements starting on December 4th). No given explanation exists to the proportionally higher daily amount of participants after December 4th, but in order to account for potential selection bias we use coarsened exact matching to only compare participants with an exact match in observable characteristics. Participants were uniquely identified by their IP-address, and in case more than one answer was registered only the first completed answer was accounted for. Although participants could have potentially answered the simulation tool before and after the inclusion of gamification, this was not observed in our sample.

The questions answered changed only depending on the simulation tool used (i.e. pension or insurance), with additional differences being attributed only to the absence or inclusion of the gamification elements. The game-elements included were a progress-bar, motivating messages and milestones (Dicheva et al., 2015; Zichermann & Cunningham, 2011; Sanchez et al., 2020; Goh et al., 2012; Huang & Soman, 2013; Singer & Schneider, 2012).

Figures 3 and 4 show examples of the adaptive learning simulation tools before and after the gamification intervention. In the tool before the intervention (Fig. 3),

[7] Compen et al. (2022) use similar simulations, but with the focus to analyse the impact of herding bias on decision-making. The authors showed randomly generated percentage numbers for one of the alternative to consumers in the treatment group that would indicate how many of their peers were selecting one of the answers. The authors note an important level of drop-outs (i.e. low completion rate) in a similar financial education setting, as such, the use of gamification appears as an appropriate method to improve completion rate.

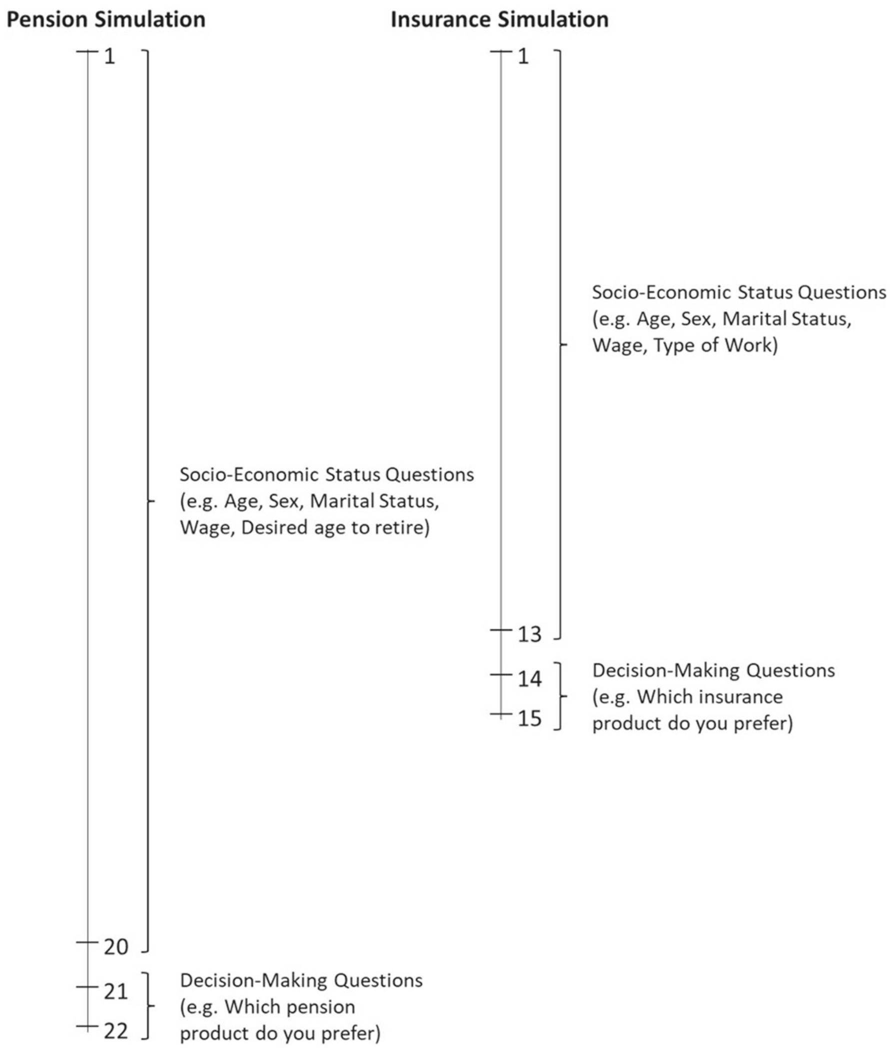

Fig. 2 Types of question answered by simulation tool

participants are asked directly for information that is relevant to provide a personalization of the required pension or insurance for the individual. This is done with an online adaptive learning system that guides participants in their answers. As seen in the example of Fig. 4, the setting with the inclusion of gamified elements (i.e. after the gamification was included in the tool) still uses a adaptive learning system to guide users, but has additional visual aids, and the incorporation of "game levels" (here, "What I earn", "What I need" and "What it costs"), used to help participants to get motivated. In the gamification setting, participant is at the end congratulated for their answers and 'rewarded' with the personalized options of insurance or pension products that is best suited for their individual needs. Although participants in the

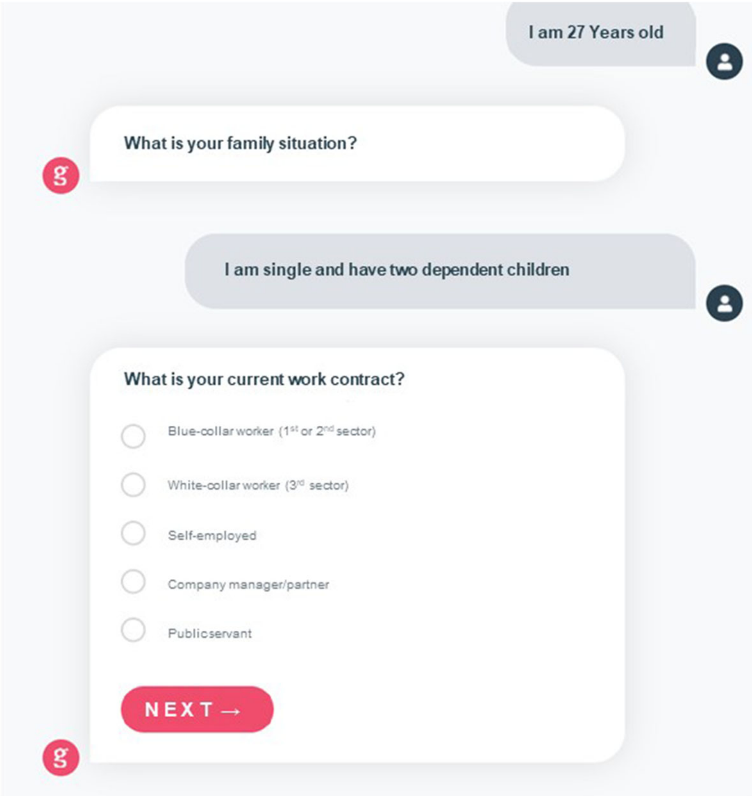

Fig. 3 Adaptive learning tool before gamification intervention

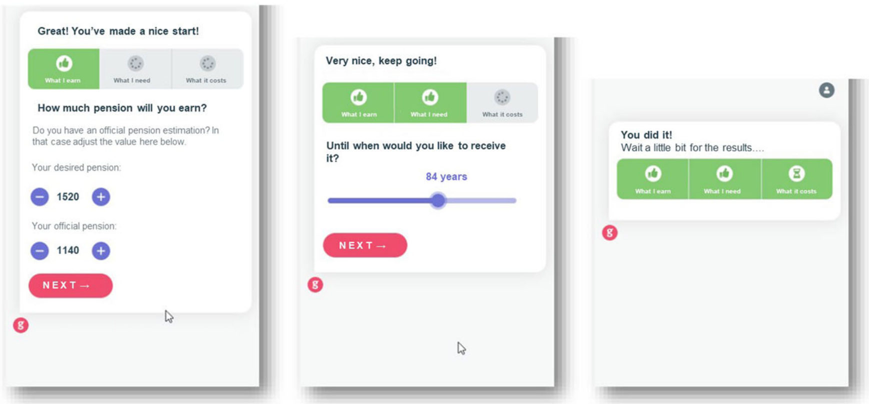

Fig. 4 Adaptive learning tool after gamification intervention

setting before the gamification intervention are asked the same questions and receive the same personalized options[8] to choose at the end of the adaptive learning tool, they receive no extra visual help, motivating message nor congratulatory sign. Despite the 'congratulatory message' and achievement of obtaining a new badge happening after each question, both their anticipation and actual realization can potentially improve the motivation to answer current and future questions. Although the motivation itself is not measured, the persistence rate is still observed on a question by question basis. Thus, by our experimental design and causal identification, any difference in persistence rate should be attributed by the inclusion of gamified elements (since it is the only major difference between the two groups in this quasi-experimental setting).

3.3 Empirical strategy and causal identification

Given the time-discontinuity, we have considered our observations in the format of time-to-event survival data, with each row representing one question answered by one of the participants in the adaptive learning experiment with time-discontinuity (i.e. before or after the gamification intervention). A binomial variable for each individual i at each question answered t indicates if participant has answered all questions up to question t. If so, we have considered it as having 'survived' at least until question t (being considered as a drop-out otherwise).

For this type of data, the Cox (1972) Proportional Hazards Model is preferred over a logit specification, since it is a more robust model that will asymptotically approximate the results for the correct specification, even not knowing the correct parametric distribution (Lin & Wei, 1989). Still, the model requires that the assumption of proportional hazards holds, which leads to misleading treatment effects in case this assumption is not met (Royston & Parmar, 2011). This assumption is tested using Schoenfeld (1980) residuals.

We have also estimated the effect of gamification to completion rate using a more general approach, that does not depend on assuming distributions nor of the proportional hazards assumption. First we have used Kaplan and Meier (1958) estimates to show the difference in survival rate graphically. To estimate quantitatively the difference in average survival rates of the adaptive learning tools with and without gamification, we have used the non-parametric restricted mean survival time (RMST) from Royston and Parmar (2013), which in addition to being more flexible also enables point estimates to have confidence intervals. $RMST$ can be intuitively seen as the integral from the area below the Kaplan-Meier estimates, yielding the average survival time for each sub-sample:

$$RMST = E\left[\min\left(T, t^*\right)\right] = \int_0^{t^*} S(t)dt \tag{1}$$

where S is the survival curve (i.e. as in Kaplan-Meier estimates), T is the number of questions answered before dropping-out. As such, $RMST$ can be seen as the expected number t^* of questions answered. To estimate the effect of gamification to the expected

[8] For the same alternatives answered.

survival time while following the adaptive learning tools, we take in (2) the difference between two $RMST$:

$$\Delta = \int_0^{t^*} S_{ag}(t)dt - \int_0^{t^*} S_{bg}(t)dt = \int_0^{t^*} \left[S_{ag}(t) - S_{bg}(t)\right] dt \tag{2}$$

where S_{ag} is the survival curve after the gamification intervention (i.e. the adaptive learning tool with game elements) and S_{bg} is the curve before the intervention. Here, Δ estimate the expected additional number of questions answered by participants in the treatment arm with gamification in comparison to the participants in the control arm (i.e. without game elements). Visually, this can be seen as the integral between the two survival curves. Equation (3) shows the restricted standard deviation survival time (RSDST):

$$RSDST = \sqrt{2\int_0^{t^*} tS(t)dt - \left[\int_0^{t^*} S(t)dt\right]^2} \tag{3}$$

Finally, we present an heterogeneity analysis to test if the effect of gamification is different depending on age, family situation, type of simulation (i.e. pension or insurance), adaptive learning tool length and type of question (i.e. socioeconomic status or decision-making).

Although the nature of our data is quasi-experimental, we do present evidence with causal claims. First, our setting uses a discontinuity in time to assign individuals either before or after the gamification intervention. This allows us to avoid the problem of self-selection and to asymptotically have similar populations before and after the time cutoff for treatment. Second, participants had no anticipation of their treatment condition. No information on the website nor on social media of the financial platform advertised the simulation with gamification. Finally, to strengthen the causal inference of our results, we used coarsened exact matching as identification strategy, which compares individuals with exact matches of both treatment conditions and approaches a fully-blocked experiment (Iacus et al., 2012). We followed the approach from Stuart (2010) by selecting variables with unbalance as matching variables.

4 Results

4.1 Data analysis

This sub-section shows the data for the whole sample (without distinction for which adaptive learning simulation tool was used). In Appendix A we show the results separately for each simulation. The data consists of 6592 participants, of which 53% (3476) were in the learning tool before and 47% (3116) were in the learning tool after the gamification intervention. Table 1 shows the descriptive statistics in terms of frequencies and the balance of the sample across the time-discontinuous experimental arms (i.e. before or after the gamification intervention). Despite the randomly set date to implement the gamification treatment, we observe (probably due to the high power

Table 1 Descriptive statistics and sample balance

	Before Gamification	After Gamification	t-test
Pension Simulation	0.884	0.806	0.077***
			(0.009)
Age Group			
Age 18-25	0.065	0.064	0.001
			(0.008)
Age 26-40	0.351	0.402	−0.051***
			(0.015)
Age 41-64	0.585	0.535	0.050**
			(0.015)
Family Situation			
Single	0.613	0.526	0.086***
			(0.013)
Cohabiting	0.164	0.202	−0.038***
			(0.010)
Married	0.223	0.272	−0.049***
			(0.011)

Note: Percentage values of different characteristics across the gamification experimental arms. We use the t-test with standard deviation in parentheses to test for balance

of the analysis) statistical differences between the variables. This is confirmed in the multinomial Wilks lambda analysis, that yields an F-test of 3.56, rejecting the null of homogeneous samples at 1% significance. For these reasons, the selected variables were used in the matching approach. However, the differences were not economically significant, since we see that the ranking (i.e. order of importance) of characteristics are still the same, with differences smaller than 9 percentage points. We show the attrition by question answered in Appendix B.

Despite not having data on access and infrastructure of digital services specific to the case of our data sample, we acknowledge that the digital divide can explain why some types of individuals from the Belgian population may be more likely to access our adaptive learning courses. This reflects the hidden costs involved in accessing courses, which include purchasing a smartphone or laptop, paying for internet, and covering energy costs. Our experiment provides a sample of individuals with different levels of age and family status, but with no specific data regarding region or income. In their yearly barometer of digital inclusion, Bonnetier et al. (2024) show that the digital divide in Belgium still exits, but that it is rapidly decreasing since 2021. For instance, while only 79% of poor residents in the Walloon region had access to home internet in 2021, this number passed to 90% in 2023, face to 90% in Brussels and 87% in Flanders regions. Still, for households with a family income above 3200 euros this number is closer to 99%. The population with the lowest degree of connectivity refers to individuals older than 55 with household income below 1400 euros. Finally, Bonnetier et al. (2024)'s report indicates that Belgium has a positive trend in internet access within the region, ranking just below the Netherlands and Luxembourg."

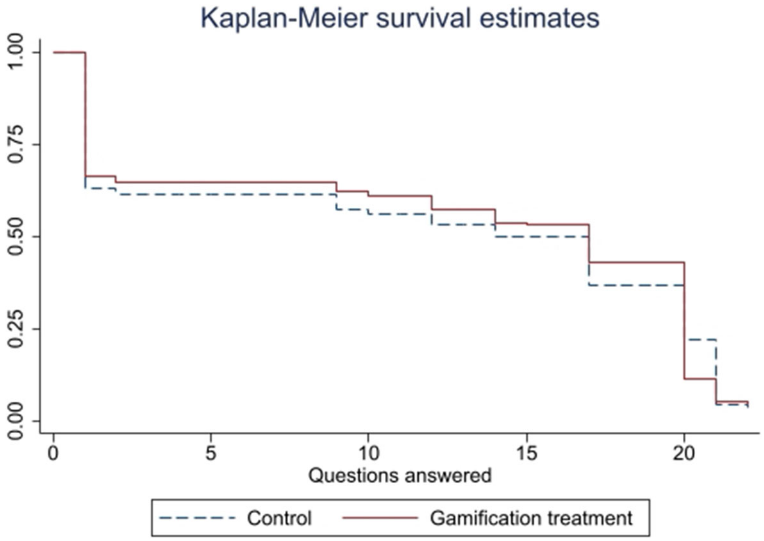

Fig. 5 Kaplan-Meier Survival estimates using full-sample

4.2 Survival analysis

We first start our analysis by testing if the proportional hazard assumption is met. The Schoenfeld (1980) residuals test yields a chi-squared of 1299, which rejects the null of proportional hazards. Considering this, the non-parametric approach is better suited for our data.

Figure 5 shows the Kaplan-Meier estimates for the full samples. The step-wise figure shows a significant drop-out rate already in the beginning and a subsequent drop near the end during the decision-making questions. Participants in the gamification treatment experienced a smaller drop-out rate during most of the adaptive learning tool duration, which is reversed during the final questions (i.e. the drop-out rate during decision-making questions appears to be higher for participants in the gamification treatment).

In Table 2 we present the results of our restricted mean survival time estimates. They confirm what was observed in the Kaplan-Meier estimates: the participants in

Table 2 Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Difference	Ratio
Full sample	11.551	12.212	0.662	1.057
	(0.077)	(0.075)	(0.107)	(0.010)

Note: The first two columns show the estimated restricted mean survival time (RMST) before gamification (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The third column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered the adaptive learning tool after the gamification intervention had a higher survival time (i.e. a higher completion rate). The third column measures the difference in effect of the gamification intervention to the number of questions answered. The survival time difference between the learning tools after and before the gamification intervention was significant, with 0.66 additional questions answered, or in terms of ratio, a number of questions answered that is 5.7% higher for the case of participants after the gamification intervention.

4.3 Heterogeneity analysis

This sub-section analyzes if the effects of gamification on completion rate also depend on background characteristics, type of question and adaptive learning tool part (i.e. initial, middle and final parts). In Table 3 we analyse the effect of background characteristics. It should be noted that for the sub-group analysis of age and family situation, we analyse the conditional average survival time. For the case of age, we observe a considerable difference for both the total survival time and the gamification effect. First, the survival time is considerably lower for younger participants, and although the difference between gamification and traditional survival times was positive, there was a large variation in the effect-sizes, not being significantly different from zero. For both 26-40 and 51-64 age ranges, the survival time and the effect-sizes were similar, reaching survival times higher than 18.4 questions answered (or 84% of the learning tool being completed), but with effect-sizes close to zero. Interestingly, despite

Table 3 Sub-group analysis - Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Difference	Ratio
Age Group				
18-25	14.780	15.030	0.251	1.017
	(0.688)	(0.627)	(0.930)	(0.064)
26-40	17.710	18.419	0.709	1.040
	(0.197)	(0.162)	(0.255)	(0.015)
41-64	18.060	17.858	−0.202	0.989
	(0.153)	(0.154)	(0.216)	(0.012)
Family Situation				
Single	7.363	8.940	1.576	1.214
	(0.107)	(0.114)	(0.156)	(0.023)
Cohabiting	18.189	18.412	0.223	1.012
	(0.194)	(0.180)	(0.265)	(0.015)
Married	18.309	18.607	0.298	1.016
	(0.165)	(0.153)	(0.225)	(0.012)

Note: Here we repeat the results from Table 2, but for sub-groups. The first two columns show the estimated restricted mean survival time (RMST) before (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The third column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered the absence of statistically significant effects, we observe that the gamification has a positive influence on younger people (who are less than 40 years old) and a negative influence on older people.

In the case of family status we observe a similar pattern. Single participants had considerably lower survival times (lower than 9.0 questions answered, or 41% of the learning tool being answered), but with the highest observed effect-size, which was of 1.6 extra questions answered. For cohabiting and married participants, the survival times were considerably higher (higher than 19.2 questions answered). In terms of the effect-sizes, the differences were close to zero.

In Table 4 we present our restricted mean survival time (RMST) results for different parts of the adaptive learning tools, i.e. the initial (first three questions), middle (questions 4 to 20) and final parts (two last questions) of the simulation tools. We do so as the questions had different natures: with initial and middle parts consisting of only socioeconomic status questions (which were used as a personalization survey that allows the adaptive learning) and the final part of only decision-making questions (which provides possible financial products of interest tailor-made to the person, considering the characteristics filled in the first part). As such, we evaluate if both the drop-out rate and the effect of gamification is different depending on behaviour differences of participants towards different types of questions and the part of the learning tool. Since participants always answered questions in the same order, it is not possible to disentangle these two effects (i.e. if it was related to the part of the learning tool or the type of question). As before, the middle and final part estimates refer to the conditional average survival time, which depend of participants answering the previous parts of the learning tool.

The initial part of the learning tool had a significant positive effect-size of additional 0.1 questions answered, while the middle part effect was close to zero. For the final part (with decision-making questions), the gamification was not effective, being even harmful, resulting in 0.3 less questions answered. The results suggests that gamification

Table 4 Adaptive learning tool length analysis - Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Total	Difference	Ratio
Initial	2.284	2.392	3	0.108	1.047
	(0.005)	(0.006)		(0.008)	(0.003)
Middle	18.095	18.177	20	0.082	1.005
	(0.057)	(0.054)		(0.079)	(0.004)
Final	20.658	20.333	22	-0.326	0.984
	(0.067)	(0.025)		(0.071)	(0.003)

Note: Here we repeat the results from Table 2, but for considering different moments of the adaptive learning tool (i.e. initial, middle, and final parts). The moments of the learning tool also correspond to different types of question, namely socio-economic questions (initial and middle part) and decision-making questions (final part). The first two columns show the estimated restricted mean survival time (RMST) before (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The total column shows the last question answered in each part of the learning tool. The third column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered works better for socioeconomic status questions and during initial and middle lengths. For decision-making questions and the last part of the learning tool, the effect of gamification seems to increase the drop-out rate. This suggests that gamification can be particularly effective during personalization surveys, which are often required in adaptive learning interventions.

5 Discussion

Although adaptive learning is particularly beneficial to learners due to its personalized nature of either content or teaching method, its common online format is usually accompanied by lower completion rates, that can lead to selection bias and meaningless results in evaluation exercises. This paper proposes a theoretical model on how gamification can affect completion rate through better behaviour and attitude. The model is tested under a quasi-experimental design with time-discontinuity to estimate the effect of gamification to increase the completion rate in online adaptive learning tools. In addition to the discontinuity in time to define treatment units, our methodology also used exact coarsened matching as identification strategy to strengthen our causal claims. To estimate effects, non-parametric survival analysis models were used, notably the restricted mean survival time approach. The online learning tool consisted of a financial education tool that was tested among 6592 adults.

Even though technology is increasingly applied in education, the excessive use of screens is associated with negative impacts to academic performance, health and emotional problems[9] (Kates et al., 2018; Melo et al., 2020). In our proposed theoretical model, we put the effects of gamification to behaviour and attitude towards adaptive learning in the centre of the discussion. We argue that this could increase the chance of students to complete education assignments with better general cognitive experience. Although not tested directly, we believe that the gamification effect to improve behaviour and attitude (which mediate the better completion rate) could be driven by an improvement in general wellbeing. A higher satisfaction in the adaptive learning environment makes it easier for students to complete education materials and the personalization surveys. The negative impact of screens can lead even to addiction or full immersion (Melo et al., 2020), but this problem can be a smaller issue for the use of gamification in short interventions, for instance on brief adaptive learning's personalization surveys (i.e. the part of our adaptive learning intervention with the highest positive effect on completion rate).

Although widely tested in the online education context, the use of gamification to improve completion rates in online adaptive learning tools is under explored. Our results indicate that gamification increased total questions answered by 5.7%, accounting for 1.6% higher completion rate. As such, the results confirm the effectiveness of gamification to reduce attrition (i.e. drop-out rate).

[9] We note that this is not always the case, since e-learning methods (like gamification) can be used to address such factors. An example is the use of gamification and augmented reality, which can have positive emotional and affective results (López-Faican & Jaen, 2020).

We performed a heterogeneity analysis to check how the effects would change in terms of treatment condition, background characteristics, type of question and adaptive learning tool length. Both young and single individuals experienced the highest effect from gamification, which can be linked to the lower attention span of younger individuals (Breeman et al., 2016). Considering this, gamification might help individuals with low attention span to stay on track and complete the adaptive learning tool. The initial and middle part of the tool (which accounted mainly for socioeconomic status and background characteristics, used as personalization survey) had positive effect-sizes from gamification, although this effect was not significant in the middle part. This suggests that gamification can be beneficial for answering personal questions, which is especially important for the case of adaptive learning interventions, which often need long personalization surveys in order to give an effective tailor-made teaching experience, suffering from early drop-outs. With the help of gamification, more learners can potentially be impacted with a fully-fledged adaptive learning content. For the final part of the online tool, that accounted for decision-making questions, the effect of gamification to completion rate was significantly negative. As a potential explanation, first, the break in expectations of simple questions answered with the help of gamifications cues to a more complex question can lead to a greater frustration of the participant leading to a higher drop-out rate. Second, the question complexity itself could also discourage participants. Finally, the preference for products offered question might be interpreted as commitment to a purchase decision, which might lead to higher drop-out rate as well. Still, more studies are needed to understand the effects of gamification in decision-making questions in contexts other than financial education. We confirm the findings from Rodrigues et al. (2022), but focusing on a particular outcome variable (i.e. completion rate), showing that the effects of gamification tend to be larger in the beginning of the intervention, but that this decreases with time (i.e. novelty effect).

The results also have policy relevance. We see how evaluation methods and experiments in general are becoming more and more important to assess education policies, materials, and methods, with low completion rates being a challenge in those evaluation efforts (since it can contaminate the evidence with selection bias). Our results shed light on how to improve this partially, since gamification interventions can be useful to reduce the drop-out rate in online learning tools.

6 Conclusion, limitations and future research

We propose and empirically test a theoretical mechanism on how gamification can increase the completion rate in adaptive learning courses due to a better behavioural response and attitude of students. The results suggest that the gamification increased the amount of questions answered by 5.7%, while completion rate increased by 1.6 percentage points.

This paper contributes to the literature in four ways. First, we show that gamification can increase the completion rate in adaptive learning interventions, even in adult financial education environments. Second, we examine who benefits most from gamification. In particular, we show that younger professionals and non-married individuals improved their completion rate by a higher degree in comparison to their counterparts. Third, we find evidence that gamification is particularly effective for adaptive learning's personalization surveys, which tend to be a significant source of dissatisfaction and reason to leave the survey. Instead, in our intervention, participants in the adaptive learning course with gamification improved their completion rate. However, this effect was not observed during more complex questions, which involved decision making. Finally, we contribute to the underlying e-learning theory, by showing that gamification provides a causal mechanism to improve completion rate through better psychological factors during adaptive learning courses (i.e. better behaviour and attitude).

We can also understand the importance of our results to the context of providing managerial recommendations that can help motivate management decisions. The first point is regarding target groups, which is fundamental in the context of a company or an educational institution providing decision support systems with adaptive learning and gamification solutions optimizing who will be the group that will benefit the most. Following our results, similar financial education courses and simulation tools with gamified elements could be better applied to younger professionals and non-married individuals, due to their better completion rates. Second, in cases where managers observe low completion rates in trainings, courses, surveys or instructions, the results from our paper suggest that gamification can be helpful during the persistence while answering socioeconomic status questions, which are usually asked in the beginning of surveys and can be a big source of attrition. Finally, it is very important for managers to understand the motivation behind individuals' decisions to participate in the course. In our case, participants joined the course to obtain information about tailor-made financial products to their needs, which was explained to the participants right before the decision-making questions, which led a considerable number of participants to leave the adaptive learning tool before the end, as discussed in Appendix B. As such, with the goal of making participants complete a course, the 'gold-pot prize' or the main source of motivation to finish the course should be delivered at the end, although partial incentives and motivations could be included throughout the course.

The limitations of the present paper give rise to further research. First, although the quasi-experimental time-discontinuous design is suitable to identify causal relationships, it still lacks the randomization of the treatment attribution. Second, the adaptive learning tool only dealt with socioeconomic status and financial decision questions. Consequently, further research is necessary to explore the external validity to other settings. Third, the order of the questions was the same for all participants, which makes it harder to disentangle the effect of gamification regarding the type of the question or the adaptive learning tool length. Next, our paper focused only on adaptive learning for adult financial education, which opens the avenue to replication of similar studies to check the effect of gamification to attrition considering different contexts, questions, research designs, sample sizes, types of public, and culture. Due to a short term intervention, the familiarization effect (i.e. the increased benefits in long-term interventions) was not observed as in Rodrigues et al. (2022). As suggested by Melo et al. (2020), the dangers of e-learning education and the constant use of screens is a fundamental topic to be addressed by the education research community.

To address the impacts of gamification and other e-learning methods to students' general wellbeing, long-term longitudinal experimental studies with causally identified effects are needed.

Appendix A: Results for each adaptive learning simulation tool separately

Figure 6 shows the Kaplan-Meier estimates for participants in the pension and Fig. 7 for those in the insurance adaptive learning simulation tools. The two figures show a significant drop-out rate already in the beginning and a subsequent drop near the end during the decision-making questions. For the pension simulation, participants in the gamification treatment experienced a smaller drop-out rate during most of the adaptive learning tool duration, which is reversed during the final questions (i.e. the drop-out rahte during decision-making questions appears to be higher for participants in the gamification treatment). In the case of the insurance simulation, this was not verified: until question 9 the drop-out rate was higher for gamification treatment participants, while at the end both treatment arms experienced similar drop-out rates.

In Table 5 we present the results of our restricted mean survival time estimates. They confirm what was observed in the Kaplan-Meier estimates: the pension simulation had a higher survival time (i.e. lower drop-out rate) for the participants in the adaptive learning tool with gamification. The difference between the survival times after and before the gamification intervention was significant, being 0.66 extra questions answered for the complete sample and 0.91 extra questions for the pension simulation. For the insurance simulation, this difference was negative, but not significant. The results indicate that gamification can indeed reduce drop-out rate, but that

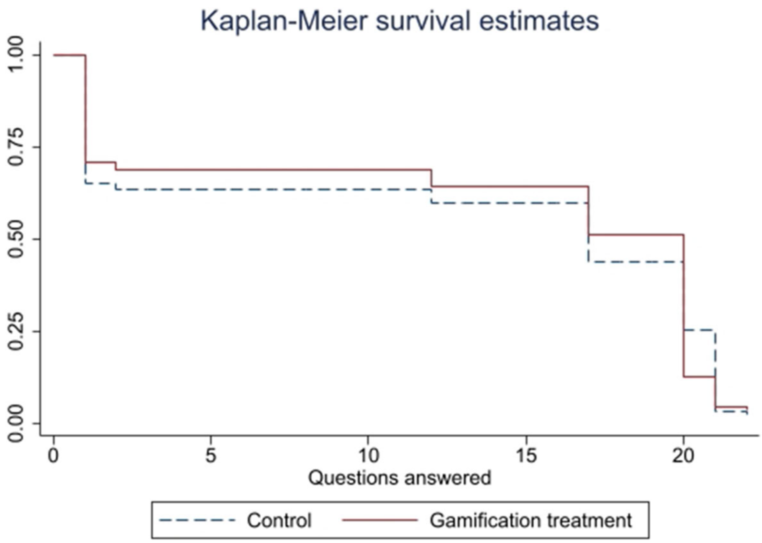

Fig. 6 Kaplan-Meier Survival estimates using pension simulation

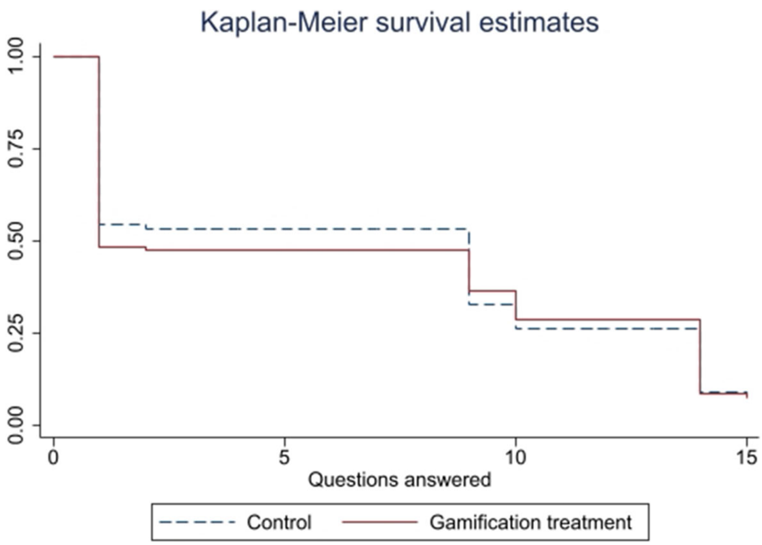

Fig. 7 Kaplan-Meier Survival estimates using insurance simulation

this can depend of the type of adaptive learning simulation tool. This difference can be due to the different demographic and the different motivation of the participants in both simulation tools.

A.1. Heterogeneity analysis

This sub-section analyzes if the effects of gamification on drop-out rate can also depend on background characteristics, type of question and adaptive learning tool length. In order to understand the interaction of those matters with our treatment variable and avoid contaminating it with effects arising from the simulation tool used, the heterogeneity analysis was done separately for each simulation tool.

Table 5 Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Total	Difference	Ratio
Pension simulation	12.569	13.481	22	0.912	1.073
	(0.075)	(0.078)		(0.108)	(0.009)
Insurance simulation	7.305	6.924	15	−0.382	0.948
	(0.179)	(0.165)		(0.243)	(0.032)

Note: The first two columns show the estimated restricted mean survival time (RMST) before (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The total column shows the adaptive learning tool length in number of questions answered. The difference column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered

In Table 6 we analyse the effect of background characteristics for the participants in the pension simulation. We note that for the age and family situation sub-group analysis, we analyse the conditional average survival time, since it depends of participants actually answering those questions, while treatment status is randomly attributed, not depending of answering a question. In the case of age, we observe a considerably difference for both the total survival time and the gamification effect. First, the survival time is considerably lower for younger participants, and although the difference between gamification and traditional survival times was positive, there was a big variation in the effect-sizes, not being significantly different from zero. For both 26-40 and 51-64 age ranges, the survival time and the effect-sizes were similar, reaching survival times higher than 18.7 questions answered, but with effect-sizes close to zero. In the case of family status, we see a similar pattern from what was observed with age. Single participants had considerably lower survival times (lower than 8.7 questions answered), but with the highest observed effect-size, which was of 1.6 extra questions answered. For cohabiting and married participants, the survival times were considerably higher (higher than 19.2 questions answered). In terms of the effect-sizes, the differences were close to zero.

Table 7 repeats the results from Table 6 for the participants in the insurance simulation. Regarding age, we also observe a smaller survival time for young participants, but the effect-sizes have different ranking. The highest effect-size point estimate was for the participants of age between 26 and 40. Still, no effect-size was significant due to the high variation. For family situation, the greatest effect-size point estimate was for single individuals, but it was also not significant.

Table 6 Pensions sub-group analysis - Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Total	Difference	Ratio
Age Group					
18-25	15.624	15.714	22	0.090	1.006
	(0.824)	(0.712)		(1.089)	(0.070)
26-40	19.045	19.007	22	−0.039	0.998
	(0.173)	(0.154)		(0.231)	(0.012)
41-64	18.907	18.738	22	−0.168	0.991
	(0.144)	(0.147)		(0.206)	(0.011)
Family Situation					
Single	7.017	8.628	22	1.611	1.230
	(0.104)	(0.114)		(0.154)	(0.024)
Cohabiting	19.211	19.354	22	0.143	1.007
	(0.161)	(0.148)		(0.219)	(0.011)
Married	19.479	19.473	22	−0.006	1.000
	(0.138)	(0.125)		(0.186)	(0.010)

Note: Here we repeat the results from Table 5, but for sub-groups. The first two columns show the estimated restricted mean survival time (RMST) before (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The third column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered

Table 7 Insurance sub-group analysis - Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Total	Difference	Ratio
Age Group					
18-25	11.878	12.370	15	0.492	1.041
	(1.028)	(1.226)		(1.600)	(0.139)
26-40	12.674	13.763	15	1.089	1.086
	(0.506)	(0.602)		(0.786)	(0.064)
41-64	12.624	13.081	15	0.457	1.036
	(0.474)	(0.435)		(0.644)	(0.052)
Family Situation					
Single	12.686	13.733	15	1.047	1.083
	(0.580)	(0.586)		(0.824)	(0.068)
Cohabiting	12.172	12.866	15	0.694	1.057
	(0.620)	(0.586)		(0.853)	(0.072)
Married	13.239	13.693	15	0.454	1.034
	(0.490)	(0.544)		(0.732)	(0.056)

Note: Here we repeat the results from Table 5, but for sub-groups. The first two columns show the estimated restricted mean survival time (RMST) before (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The third column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered

In Table 8 we present our RMST results for different adaptive learning tool length, i.e. the initial, middle and final part of the adaptive learning tools. Additionally, the questions had different types depending on the length, with initial and middle parts consisting of only socioeconomic status questions (i.e. used to provided personalized learning afterwords) and the final part of only decision-making questions (i.e. with personalized options given participant's characteristics). As in the case of the characteristics sub-group analysis, the middle and final part estimates refer to the conditional average survival time, which depend of participants answering the previous parts of the adaptive learning tool. For the pension simulation, the initial part of the tool had a significant positive effect-size of additional 0.1 questions answered, while the middle part effect was close to zero. For the case of the final part (with decision-making questions), the gamification resulted in 0.3 less questions answered. The situation was different for the insurance simulation, with a negative significant effect on the initial part of 0.1 fewer questions answered, and a positive effect-size of additional 0.4 questions answered in the middle part. The final part also had a negative effect-size, but was not significant. The results suggests us that gamification works better for socioeconomic status questions and during initial and middle lengths, but that this can depend from the type of adaptive learning simulation tool being answered (i.e. in insurance and pension simulations, slightly different questions are answered, which might motivate a higher drop-out rate), since in the insurance simulation case the effect-size was negative in the initial part of the adaptive learning tool. For decision-making questions the effect of gamification seems to increase drop-out rate.

Table 8 Adaptive learning tool length analysis - Restricted mean survival time (RMST) estimation

	Before Gamification	After Gamification	Total	Difference	Ratio
Pension Simulation					
Initial	2.284	2.392	3	0.108	1.047
	(0.005)	(0.006)		(0.008)	(0.003)
Middle	18.095	18.177	20	0.082	1.005
	(0.057)	(0.054)		(0.079)	(0.004)
Final	20.658	20.333	22	−0.326	0.984
	(0.067)	(0.025)		(0.071)	(0.003)
Insurance Simulation					
Initial	2.077	1.959	3	−0.118	0.943
	(0.009)	(0.008)		(0.012)	(0.006)
Middle	10.589	10.979	13	0.390	1.037
	(0.128)	(0.119)		(0.175)	(0.017)
Final	14.342	14.295	15	−0.047	0.997
	(0.149)	(0.152)		(0.213)	(0.015)

Note: Here we repeat the results from Table 2, but for considering different moments of the adaptive learning tool (i.e. initial, middle, and final parts). The moments of the adaptive learning tool also correspond to different types of question, namely socio-economic questions (initial and middle part) and decision-making questions (final part). The first two columns show the estimated restricted mean survival time (RMST) before (BG) and after gamification (AG). The numbers are the average number of questions answered, with standard deviation in parenthesis. The total column shows the last question answered in each part of the adaptive learning tool. The third column shows the difference $AG - BG$ while the last column shows the ratio $\frac{AG}{BG}$, both in terms of questions answered

Appendix B: Attrition by question answered

As the main interest variable, Table 9 shows the total attrition per question answered in the adaptive learning tool with and without gamification. The continuous survival rate represents the percentage of participants that did not drop-out until question t. Both experimental conditions after the first question answered (which was "what is your age?") had a fairly low survival rate, of 59.9% for the adaptive learning tool before the gamification and 66.3% for the adaptive learning tool after the gamification intervention. Except for question 20, all other questions had higher continuous survival rates for the participants in the tool with gamification. At the end of all 22 questions, the final survival rate was 4.4% for the tool with game elements and 2.8% for the tool before the gamification intervention, a difference of 1.6% smaller drop-out rate for participants in the adaptive learning tool after the gamification intervention.

We note that a high number of participants (close to 40%) decided to drop-out already in the first question. Although we cannot know for sure the motivation of an early drop-out, we believe it might be due to either (i) the realization of entering a long simulation; (ii) believing that the first question (i.e. 'what is your age?') is too personal; (iii) selecting the wrong simulation tool; (iv) clicking by mistake in the simulation tool link, without the desire to participate.

Table 9 Attrition of sample

	Before Gamification	Survival rate	After Gamification	Survival rate
Q1	2082	0.599	2067	0.663
Q2	2016	0.580	2009	0.645
Q3	2016	0.580	2009	0.645
Q4	2016	0.580	2009	0.645
Q5	2016	0.580	2009	0.645
Q6	2016	0.580	2009	0.645
Q7	2016	0.580	2009	0.645
Q8	2016	0.580	2009	0.645
Q9	1924	0.554	1943	0.624
Q10	1894	0.545	1896	0.608
Q11	1894	0.545	1896	0.608
Q12	1782	0.513	1786	0.573
Q13	1782	0.513	1786	0.573
Q14	1704	0.490	1664	0.534
Q15	1701	0.489	1658	0.532
Q16	1701	0.489	1658	0.532
Q17	1263	0.363	1334	0.428
Q18	1263	0.363	1334	0.428
Q19	1263	0.363	1334	0.428
Q20	746	0.215	359	0.115
Q21	128	0.037	160	0.051
Q22	98	0.028	138	0.044

Note: Here we show the amount of participants that answered each question for the experimental arms before and after gamification. The first number refers to the total number, and the second to the percentual survival rate related to the total sample that started the adaptive learning tool

Besides, a high number of participants also did not complete the adaptive learning tool (more than 95%). Besides the lack of motivation during the initial questions that led to an early drop-out, we believe that the decision-making questions had a considerable impact to increase the drop-out rate for three possible reasons: (i) by showing the three possible financial products (i.e. either of insurance or pension), the participants already obtained their desired information, and did not feel compelled to select a preference; (ii) the participant might have believed that selecting a preference would entail a commercial commitment to that product, which was not the case; (iii) frustration to answer a cognitively intensive question after questions with low-cognitive effort (i.e. socio-economic status). Even though this apparent high drop-out rate may feel strange, we must note that many online learning platforms and technologies (e.g. such as in MOOCs) experience very low completion rates, that can be as low as 0.7% for certain MOOCs (Jordan, 2015). Finally, although to the optic of the adaptive learning tool it was only finished at either question 15 (for participants in the insurance simulation tool) or 22 (for participants in the pensions simulation tool), participants obtained their necessary information earlier (i.e. question 13 in the insurance course and question 20 in the pension course). As such, noting that participation was fully voluntary and that their intrinsic motivations to join in the simulations was related to obtain simulated values about financial products regarding their needs, the completion rate of their personal objective was considerably higher.

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Data Availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval For the experiment was granted by the Social and Societal Ethics Committee of the KU Leuven (G-2019 121,923).

Conflicts of interest The authors declare that the work has no conflict of interest.

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