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IMPACT OF INCENTIVE ORIENTATED BLENDED LEARNING ON STUDENTS' LEARNING BEHAVIOR AND OUTCOMES

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Abstract:
This paper focuses on a blended learning approach implemented in university courses with the aim to improve learning performance and outcomes. Therefore, a simple theoretic model of dynamic optimization is developed. In addition to the created online learning opportunities, an incentive based approach aims to promote student engagement in courses. Due to this incentive based blended learning concept, the learning process becomes more effective and successful. Moreover, students' motivation to deal with the teaching material rises. Consequently, the lack of preparation often resulting in poor student performance diminishes. For this purpose the concept of learning by doing is introduced to university courses supported by incentive orientated blended learning. Therefore, exam outcomes are mainly the result of knowledge, which rises in solving exercises and spending learning time. Dynamic maximization of utility considering the choice between learning time and leisure time is performed. Depending on preferences for leisure time, learning performance varies. As a result, utility is maximized by constant learning over time rather than by last minute learning. This paper emphasizes the importance of the interplay of incentives to learn, e-learning opportunities and face-to-face-sessions in regard to better learning behavior and outcomes.

Keywords: blended learning, e-learning, incentives, learning by doing, student engagement, student outcome

1. INTRODUCTION

Since traditional teaching methods are taken up by the new trend towards online learning, blended learning becomes more important. Blended learning combines face to face sessions and e-learning opportunities and thus meets these growing expectations and needs for better learning opportunities and outcomes (Garrison & Kanuka, 2004). This trend is confirmed by various surveys which show that online learning tools in students' learning experiences have increased significantly (Allen & Seaman, 2006).

The high growth rate of online learning strategies is driven by supply and demand side reasons. On the one hand, university teachers benefit from economies of scale and scope in teaching a large number of students (Twigg, 2013; Morris, 2008). On the other hand, students show a new attitude towards online learning (Sebastianelli & Tamimi, 2011) and a reduced engagement with face to face education (Exetere et al., 2010).

In order to develop a simple model this paper makes use of the concept learning by doing to show the influence of blended learning on learning behavior, growth of knowledge and the resulting outcomes. Until now, economic literature has only focused on learning by doing within the field of production. In this context, learning by doing was first introduced in 1962 by Arrow describing learning as a product of experiences, which is gained during the process of problem solving. Arrow shows that knowledge is growing in time due to improvement in performance. Göcke (2002) extends this model by analyzing the optimal allocation of time between working and leisure in the context of learning by doing.

This paper introduces a simple model of learning by doing in the context of university courses with dynamic optimization. The exam outcome depends on knowledge accumulation during the learning period. Thereby, blended learning creates learning opportunities which are available 24 hours per day during 7 days per week. In addition, preliminary testimonials provide incentives to early learning and consequently boost the engagement in blended learning due to rewards. While solving blended learning exercises, students acquire knowledge and human capital is accumulated. However, students have to decide upon the optimal time allocation to learning and leisure which differs in utility formulation. This model shows similarities to Göcke (2002), yet learning by doing is applied to university courses instead of production. While working is limited by consumption of goods, growth of knowledge shows no limits. Furthermore, the choice between working/learning and leisure is not the main concern of this paper. This trade-off just curtails spending total time for learning.

Thus, we address the question how incentive orientated blended learning influences and improves learning behavior and exam outcomes.

2. THE MODEL

This paper introduces the concept of learning by doing to university courses supported by incentive orientated blended learning. Besides face-to-face-sessions students have the possibility to solve online exercises during the semester in order to improve their knowledge with the aim to pass the exam.

2.1 Growth rate of knowledge

We assume that knowledge ξ is a differentiable function of time t fulfilling the ordinary differential equation

$$\frac{d}{dt}\xi = a(E, q), \tag{1}$$

where a denotes the growth rate of knowledge depending on the learning activity of the student. We assume that the student uses the blended learning platform to solve exercises. Here, the relative learning time $q = q(t)$ describes the fraction of time the student spends using the online learning opportunities at time t. Clearly, the values of q belong to the interval $[0,1]$. Roughly speaking, a student who learns without breaks yields $q(t) = 1$. In this case his leisure time $1 - q$ equals zero. The parameter E models the number of exercises solved by the student per time unit. Thus, the accumulation of knowledge via learning by doing results as a by-product of solving exercises. Keeping this in mind, we suppose a is differentiable and that a satisfies

$$\frac{\partial \mathrm{a}}{\partial \mathrm{E}}(\mathrm{E},\mathrm{q}) > 0, \quad \frac{\partial \mathrm{a}}{\partial \mathrm{q}}(\mathrm{E},\mathrm{q}) \gtreqless 0 \ \text{ whenever } \ \mathrm{q} \lesseqgtr \mathrm{q}_0$$

for some $\mathrm{q}_0 \in (0,1)$. However, if a critical relative learning time q_0 is exceeded, the productivity decreases by the absence of pauses.

The number of exercises students can solve per time unit depends on their expertise and the time spent for learning. This leads us to treat E as a function of ξ and q which shall fufill

$$\frac{\partial \mathrm{E}}{\partial \xi}(\xi,\mathrm{q}) > 0, \quad \frac{\partial \mathrm{E}}{\partial \mathrm{q}}(\xi,\mathrm{q}) > 0.$$

The dependency on q models for small q the concentration increase with respect to the relative learning time.

In the following, we apply a simple concrete model by choosing

$$\mathrm{a}(\mathrm{E},\mathrm{q}) = \xi\mathrm{q}(1-\mathrm{q}) \quad \text{and} \quad \mathrm{E}(\xi,\mathrm{q}) = \mathrm{Eq}.$$

Now, we can directly solve Equation (1) by

$$\xi(\mathrm{t}) = \xi(0)\exp\left(\int_0^{\mathrm{t}} \mathrm{q}\,(\mathrm{s})^2\big(1-\mathrm{q}(\mathrm{s})\big)\mathrm{ds}\right).$$

2.2 The exam and the utility function

Since utility is a result of the accumulated knowledge and leisure as the residual of learning time, the utility function of a student writing the exam at time T is given by

$$\mathrm{u} := \mathrm{X} + \mathrm{X}_t - \gamma \int_0^{\mathrm{T}} \mathrm{q}\,(\mathrm{t})e^{-\delta(\mathrm{t}-\mathrm{t}_0)}\mathrm{dt}$$

or some $\gamma, \delta \geq 0$ and $0 < \mathrm{t}_0 < \mathrm{T}$, where X is the result of the exam and X_t the result of the preliminary testimonial. We use the convention that $\mathrm{X} = 1$ represents the best mark and $\mathrm{X} = \mathrm{X}_0 = 1/2$ the least mark such that the student has passed the exam. Therefore, we expect $\mathrm{X} \in \{0\} \cup [1/2,1]$. Here, $\mathrm{X} = 0$ means failed.

Utility decreases with time spent on learning q, since a high learning activity results in less leisure time. Furthermore, the term $e^{-\delta(\mathrm{t}-\mathrm{t}_0)}$ models individual time preferences. If the student prefers to organize his learning activity long-term, we assume $\delta = 0$, resulting in a diminishing exponent. In contrast, $\delta > 0$ is assumed, if the student prefers to learn short-term. In comparison to case $\delta = 0$, learning is more taxing and exhausting for $\mathrm{t} < \mathrm{t}_0$ and easier for $\mathrm{t} > \mathrm{t}_0$ according to his disutility for early learning.

The result of the exam depends on the knowledge of the student at time T and thus, we interpret X as a function of ξ. However, this dependency is not directly given, since it is not possible for the student to predict the result of the exam before writing it. Therefore, we need to introduce an additional parameter ϵ for the uncertainty modelling the luck, concentration and further unpredictable influences. We assume

$$\mathrm{X}(\xi,\epsilon) = \begin{cases} 0 & \text{if } \xi + \epsilon < \frac{1}{2}, \\ 1 & \text{if } \xi + \epsilon > 1, \\ \xi + \epsilon & \text{else,} \end{cases}$$

as a simple choice for the result function of the exam.

2.3 Utility maximization without testimonial

Since utility depends on time spent on learning and leisure, utility is maximized by the choice of learning time q. As a baseline, we firstly determine the optimal choice of learning time q without taking preliminary testimonials into account. Section 2.4 examines dynamic optimization with preliminary testimonials, so that both results can be compared.

However, the result function of the exam $X(\xi, \epsilon)$ includes four cases, which lead to different utility maximizing time allocations q. First, the student maximizes his utility without considering to fail or to pass with the best mark. Secondly, the student fails the exam. Thirdly, the student's concern is to pass the exam satisfied with the lowest mark and fourthly, the student wants to pass the exam with the best mark. We have chosen this order with the aim to start with the average and most common student, who wants to pass the exam as successful as possible maximizing his utility and end with the more rare cases, students who fail or pass with the best or lowest mark.

The first case deals with a student, who wants to pass the exam as successful as possible, but who does not expect to achieve the best mark. This case is given by $1/2 > \xi + \epsilon \leq 1$; hence, the student passes the exam with a mark below the best mark. Given that $X(\xi, \epsilon) = \xi + \epsilon$, we can derive the utility function as

$$u(q, \epsilon) = \xi(T) + \epsilon - \gamma \int_0^T q\,(t) e^{-\delta(t-t_0)} dt.$$

The first order condition for maximization is given by

$$\frac{d}{ds} u(q + sv)|_{s=0} = \xi_0 \int_0^T (\,2qv - 3q^2 v) dt \cdot \exp\left(\int_0^T q^2\,(1-q) dt \right) - \gamma \int_0^T v\, e^{-\delta(t-t_0)} dt \overset{!}{=} 0$$

for all $v = v(t)$, which implies

$$\xi_0 q(t)(2 - 3q(t)) \exp\left(\int_0^T q^2\,(1-q) dt' \right) = \gamma e^{\delta t_0} e^{-\delta t}. \tag{2}$$

Note that the factor $\exp\left(\int_0^T q^2(1-q) dt\right)$ is independent of time and can therefore be treated as a constant. Defining

$$C := 3 \frac{\gamma e^{\delta t_0}}{\xi_0} \exp\left(- \int_0^T q^2\,(1-q) dt' \right),$$

we derive $q(t) = 1/3\left(1 \pm \sqrt{1 - Ce^{-\delta t}}\right)$ by solving Equation (2), which can be rewritten in use of the parameter C as $9q(t)^2 - 6q(t) + Ce^{-\delta t} = 0$. The second order condition for a maximum is given by

$$\frac{d^2}{ds^2} u(q + sv)|_{s=0} = \left(\xi_0 \int_0^T 2\, v^2 (1 - 3q) dt + \xi_0 \left(\int_0^T v\,(2q - 3q^2) dt \right)^2 \right) \exp\left(\int_0^T q^2\,(1-q) dt \right) \leq 0$$

Since the second term is always non-negative, the first term has to be ≤ 0 for a utility maximum, which is true for $q \geq 1/3$. Consequently, this leads to the utility maximizing

$$q(t) = \frac{1}{3}\left(1 + \sqrt{1 - Ce^{-\delta t}}\right).$$

Next, we take a closer look at the second case which is given by $\xi + \epsilon < \frac{1}{2}$. Therefore, the student is not able to pass the exam.

As we have shown, knowledge at time T is maximized by a constant $\mathrm{q} = 2/3$. Therefore, the student is not able to pass the exam if $1/2 - \epsilon > \xi_{\mathrm{opt}}(\mathrm{T}) := \xi_0 \exp 4/27\,\mathrm{T}$. This inequality depends on the uncertainty parameter ϵ which has the range $[-\epsilon_0, \epsilon_0]$. Consequently, $\mathrm{q} = 0$ maximizes the utility function of the student for $1/2 - \epsilon_0 > \xi_{\mathrm{opt}}(\mathrm{T})$ being independent of ξ. Furthermore, in the case of $1/2 - \epsilon_0 \leq \xi_{\mathrm{opt}}(\mathrm{T}) < 1/2 + \epsilon_0$ the student depends on luck. Assuming that the student does not believe in luck, again $\mathrm{q} = 0$ represents the utility maximizing choice of learning time.

Within the third case we consider an unmotivated student, whose only aim is to pass the exam without being interested in a good mark. This case is described by $\xi(\mathrm{T}) = 1/2 - \epsilon$. Since this equation again depends on the student's expectation of the uncertainty parameter ϵ, the determination of the utility maximizing q varies according to different risk attitudes.

Hence, we maximize u under the constraint $\xi(\mathrm{T}) = 1/2 + \epsilon$. In order to compute the utility maximizing q for this case, we apply the method of Lagrange multipliers.

$$\mathrm{L}(\mathrm{q}, \lambda) = \frac{1}{2} + \epsilon - \gamma \int_0^{\mathrm{T}} \mathrm{e}^{-\delta(\mathrm{t}-\mathrm{t}_0)}\, \mathrm{q}\mathrm{d}\mathrm{t} + \lambda(\xi(\mathrm{T}) - \frac{1}{2} - \epsilon$$

If we assume the existence of a utility maximizing q, we have these two conditions:

$$\frac{\mathrm{d}}{\mathrm{ds}} \mathrm{L}(\mathrm{q} + \mathrm{sv}, \lambda)|_{\mathrm{s}=0} \overset{!}{=} 0, \qquad \text{for all } \mathrm{v} = \mathrm{v}(\mathrm{t}),$$
$$\frac{\mathrm{d}}{\mathrm{d}\lambda} \mathrm{L}(\mathrm{q}, \lambda) = \xi(\mathrm{T}) - \frac{1}{2} + \epsilon \overset{!}{=} 0.$$

Furthermore, assuming the existence of a utility maximizing q, utility is maximized by

$$\mathrm{q}_{\pm}(\mathrm{t}) = \frac{1}{3}\left(1 \pm \sqrt{1 - \frac{6\gamma \mathrm{e}^{-\delta \mathrm{t}}}{\lambda(1 - 2\epsilon)}}\right).$$

Assuming that the students learning capability is below average, the student needs to learn close to the knowledge optimizing $\mathrm{q} = 2/3$. This implies that we can neglect q_{-}.

Finally, the last case is given by a highly ambitious student who aims to pass the exam with the best mark and thinks that he is able to do so. This case is characterized by $\xi + \epsilon > 1$, consequently the student passed the exam achieving the best mark. If $\mathrm{X}(\xi, \epsilon) = 1$ holds, the utility function is given by

$$\mathrm{u}(\mathrm{q}, \epsilon) = 1 - \gamma \int_0^{\mathrm{T}} \mathrm{q}\,(\mathrm{t}) \mathrm{e}^{-\delta(\mathrm{t}-\mathrm{t}_0)} \mathrm{d}\mathrm{t}$$

This case is very similar to the third case, because we again apply the method of Lagrange multipliers. In order to compute the optimal learning time q utility is maximized under the constraint $\xi(\mathrm{T}) = 1 + \epsilon$.

2.4 Utility maximization with testimonial

In order to illustrate the impact of preliminary testimonials on learning behavior, X_{t} as the result of the preliminary testimonial is added to the utility function. With the aim to reduce complexity, we consider only one preliminary testimonial at a certain time. The preliminary testimonial takes place at time $0 < \tau < \mathrm{T}$ in order to provide incentives to early learning. If the student passes the exam, the result of the testimonial improves the exam mark. But a successful testimonial is not credited, if the student fails the exam.

For reasons of simplicity, a successful result of the testimonial has no influence on the result-function of the exam, but it increases utility with the summand X_{t}. If the student does not pass the testimonial, this result has no influence on his or her utility. Nevertheless, a successful result increases utility and is therefore considered as desirable.

Hence, in this context utility changes to

$$u = X + X_t - \gamma \int_0^T e^{-\delta(t-t_0)}\, q dt.$$

Since, the result of the testimonial counts less than the exam, it is weighted with α. In addition, the result of the exam depends on the initial level of knowledge ξ_0, the uncertainty parameter ϵ_t and the accumulated knowledge until the date of the testimonial τ. Thus, we have

$$X_t = \alpha\xi(\tau) + \epsilon_t = \epsilon_t + \alpha\xi_0 \exp\left(\int_0^\tau q^2\,(1-q)ds\right).$$

As in Section 2.3 described, the result function of the exam includes four cases, which lead to different utility maximizing time allocations q. Since the first case represents the most frequent student, this case is computed in detail hereafter. The remaining three cases do not need exact calculation, as the influence of the testimonial can be derived causally.

Likewise to the utility maximization without testimonial, the first case describes a student, whose aim is to pass the exam as successful as possible by maximizing utility without considering the best mark. Thus, following the computation in Section 2.3 and defining analogously

$$C(\alpha) := 3\frac{\gamma}{\xi_0}\left(\exp\left(\int_0^T q^2\,(1-q)ds\right) + \alpha \exp\left(\int_0^\tau q^2\,(1-q)ds\right)\right)^{-1},$$

derivation leads to utility maximizing learning time

$$q(t) = \frac{1}{3}\left(1 + \sqrt{1 - C(K)e^{-\delta t}}\right)$$

for $K = \alpha$ if $t \leq \tau$ and $K = 0$ if $t > \tau$.

The second case is given by a student who is not able to pass the exam. This case does not differ from utility maximization without testimonial, since the result of the testimonial only improves the mark and does not influence the passing of the exam. Within the third case we consider a student whose main priority is to pass the exam without being interested in a good mark. Assuming a passed testimonial, the student achieves a better mark, because if he or she passes the exam the result of the testimonial improves his or her mark. However, since the student is not interested in a good mark, the preliminary testimonial does not change his or her learning behavior.

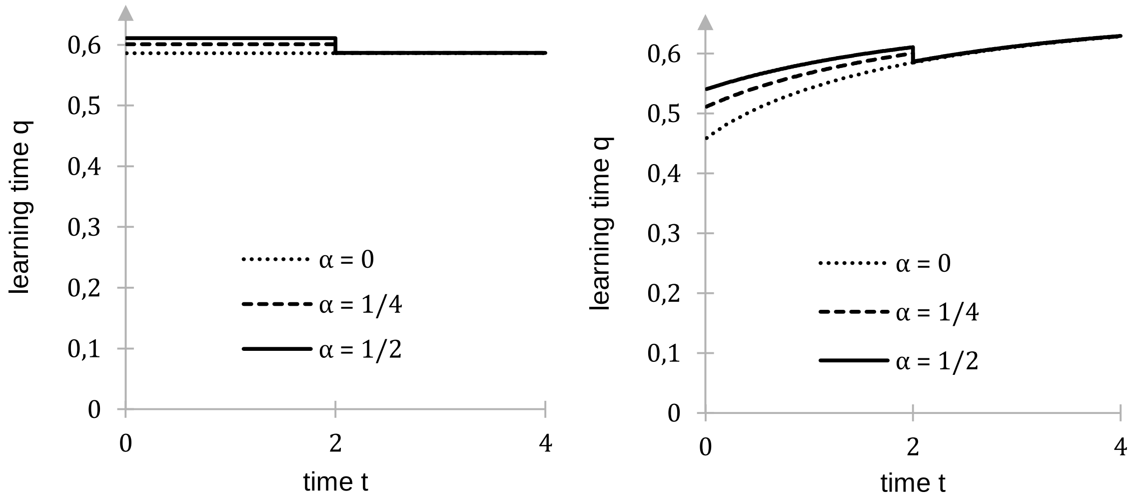
The fourth case deals with a highly ambitious student, who wants to achieve the best mark. Since this type learns constant and early and since the result of the testimonial improves his exam mark, he or she is able to learn less in order to achieve the best mark.

Consequently, the introduction of a preliminary testimonial leads to an improvement of learning performance and outcomes in the first and second case. Nevertheless, in the fourth case students achieve the best mark, despite learning less.

2.5 Results

Figure 1 compares the utility maximizing q-functions with and without testimonial for both types of students: Each figure shows one graph in the case of no testimonial ($\alpha = 0$), a second graph for $\alpha = 0.25$ and a third graph for $\alpha = 0.5$ varying the value of the preliminary testimonial. As time frame we assume one semester comprising four months, with a preliminary testimonial in the half of the semester after two months.

Figure 1: Graph of the optimal q for $\delta = 0,\ \xi_0 = 1/3,\ \gamma = 1/12, \tau = t_0 = 2, T = 4$ (left) and for $\delta = 1/2 \cdot log(2)$, $\xi_0 = 1/3,\ \gamma = 1/12,\ \tau = t_0 = 2, T = 4$ (right).



In the case of $\delta = 0$ denoting preferences for long-term learning the utility maximizing q-functions are illustrated in Figure 1 (left). As a result utility is maximized by a constant learning time q per unit during the time period without testimonial. Furthermore, introducing a testimonial, the fraction of learning time remains constant in time before and after the testimonial. Nevertheless, it is characterized by a step at the time of the testimonial with a higher level before the testimonial. The level of learning time before the testimonial is even higher for increasing values of α. Therefore, a higher value of the testimonial leads to a higher learning activity before the testimonial.

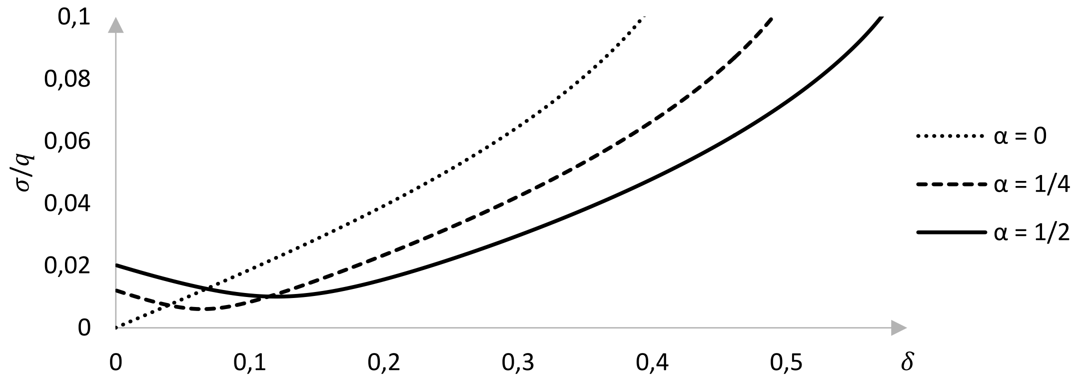
The utility maximizing q-functions in the case of $\delta = 1$ denoting preferences for short-term learning are illustrated on the right of Figure 1. In contrast to the left part of Figure 1, they are characterized by a little increase of q in t during the semester. Moreover, assuming a preliminary testimonial there is a step at the time of the testimonial with a higher overall level of q before the testimonial. Furthermore, the overall level of q before the testimonial increases with the value of the testimonial. Although, the choice of learning time q is not a constant function in time and despite preferences for short-term learning, last minute learning is avoided with and without testimonial.

In order to establish a measure for the consistency of learning, we define the variance

$$\sigma^2 = \frac{1}{T}\int_0^T (q - \overline{q})^2 dt$$

with $\overline{q} = \frac{1}{T}\int_0^T q\,dt$ being the mean value of q. Figure 2 plots the relative standard deviation $\sigma/\overline{q}$ against δ. Furthermore, the figure shows one graph in the case of no testimonial ($\alpha = 0$), a second graph for $\alpha = 0.25$ and a third graph for $\alpha = 0.5$. Thus, we vary the value of the preliminary testimonial likewise to Figure 1.

Figure 2: Graph of the relative standard deviation $\sigma/\overline{q}$ as a function of δ for $\xi_0 = 1/3,\ \gamma = 1/12,\ \tau = t_0 = 2$ and $T = 4$.



The learning activity of students with preferences for long-term learning with $\delta = 0$ is totally constant without a testimonial. In contrast to this, a preliminary testimonial encourages students to learn more before the testimonial leading to a higher relative standard deviation. This effect is enhanced with increasing values for α.

In the case of preferences for short-term learning and without a preliminary testimonial the consistency of learning time decreases with increasing δ. In contrast to this fact, the existence of a preliminary testimonial leads to a rise of the consistency of learning behavior with increasing values for α. Thus, the more important the testimonial becomes the more constant the learning activity becomes (after a critical value of δ). This effect is even stronger the higher preferences for short-term learning are.

These results support our concern to emphasize the importance of blended learning and preliminary testimonials leading to effective learning behavior and better learning outcomes. In this context, research in cognitive psychology has proved that the best learning outcomes are realized by repeating course contents every day at a manageable level (Ebbinghaus, 1885). Consequently, the resulting utility maximizing learning time of both types of students leads to better learning outcomes and the blended learning opportunities fully meet the demands of an optimal learning environment.

3 CONCLUSION

This paper has analyzed a simple model based on learning by doing in the context of university courses. Since exam outcomes depend on accumulated knowledge, the offered range of blended learning enables around-the-clock learning opportunities and a successful preliminary testimonial entails the possibility to improve the exam outcome. Depending on individual preferences for time management, students decide upon the optimal time allocation of learning and leisure.

Considering dynamic utility maximization without testimonial, a (nearly) constant learning activity over time results in the case of preferences for long- and even short-term learning. However, there is just a little increase of q in t for students who organize their learning activity short-term. Nevertheless, last minute learning is avoided. As research in cognitive psychology has shown, learning at intervals in a longer time frame with more repetition is far more effective than last minute learning.

Assuming a preliminary testimonial, students again choose a constant learning activity over time. However, the overall level of learning time is higher before the testimonial. Therefore, blended learning combined with a preliminary testimonial enhances the effect of early learning instead of last minute learning. In addition, an improvement of exam outcomes results for all students who pass the exam. Yet students who would pass the exam with the best mark learn less.

Concluding, we are able to show that learning behavior and exam outcomes become more effective and successful as a consequence of incentivizing testimonials and around-the-clock learning opportunities.

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