Nudging Digital Learning – An Experimental Analysis of Social Nudges to Manage Self-Regulated Learning and Online Learning Success

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Abstract

Self-regulated learning competencies are of increasing importance to ensure learning success in online learning environments. We investigate the use of digital social nudges in a self-reliant online learning situation to support learners in better managing their self-regulated learning behaviors. We ground our research on dual-process theory and social comparison theory to design social nudges. To evaluate our research model, we conduct an online experiment (N=226). The results show that social nudges positively impact learning outcomes mediated by self-regulated learning behaviors manifested using learning strategies. We found that positive emotions can further strengthen the positive effect of social nudges. Our results help to understand how social nudges can be efficiently used in online learning environments to support learners in better managing their learning processes and achieving learning outcomes. We open new chances for researchers and designers of online learning materials to support online learning processes.

Keywords: Social Nudging, Self-Regulated Learning, Online Learning, Nudging, Experiment.

1. Introduction

Over the last decades, online learning has gained increasing attention and importance. Nowadays, circumstances such as the Covid-19-pandemic highlight the importance but also the need for high-quality online learning (Adedoyin & Soykan, 2020). Online learning environments are overcoming barriers of time and place and allow for an interactive design. Additionally, online learning has emerged as a cost-effective way to deliver training at convenient times to a large number of employees in various locations (Wan et al., 2012). Companies support integrating more online learning to train their employees (57%) and at the same time employees ask for a more self-learning experience (58%; Nestor, 2021). In company settings, a growing number of employees are seeking learning opportunities to upgrade their competencies (Wan et al., 2012). Once seeking for learning materials, individuals have multiple sources of information with a non-linear structure and interactivity of open information systems resulting in greater difficulties for learners (Narciss et al., 2007). In such situations, learners are asked to self-regulate their own learning process. Self-regulated learning can be understood as a self-initiated usage of cognitive learning strategies and regulatory strategies to control cognition and manage resources (Yen et al., 2018). Self-regulating the own learning process requires one to be capable of guiding the own learning process. Guiding instructions can help learners to better manage their self-regulated learning in which teachers are not available to give instructions (Morgan-Thomas & Dudau, 2019). Research has demonstrated, that learners with self-regulated learning competencies are more successful in learning with digital media (Broadbent & Poon, 2015). Furthermore, the Organization for Economic Co-operation and Development shares this viewpoint by presenting a framework that integrates “self-regulation” and “learning-to-learn” skills as core elements (OECD, 2019). Among others, self-regulation is an essential capability for individuals to seek solutions to difficult problems (Littlejohn et al., 2012).

In addition to its importance, regulating the own learning process can be challenging to learners because knowledge about self-regulated learning and learning strategies’ application is required (Perels & Dörrenbächer, 2018). From a learner’s perspective, regulating the own learning process requires active, reflective, and conscious cognitive management and this turns out to be time-consuming and effortful (Pintrich, 1995). Thus, learners often lack the motivation to even use supportive features for applying self-regulated learning strategies and they tend to ignore tools designed and provided for them (Cho, 2004). One potential solution to better manage a self-regulated learning process is to use the concept of digital nudging

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(Bourguet et al., 2022). Digital nudging can be described as "*the use of user-interface design elements to guide people's behavior in the digital choice environment*" (Weinmann et al., 2016, 433). Although digital nudges can be effective, it is important to carefully decide about their design. Social nudges do not lead to positive effects in every case. In educational research, also no effects of social nudges on learning outcomes could be observed (Brown et al., 2019), and also in comparative persuasive designed environments, effects vary depending on the competitive structure of social comparison (Santhanam et al., 2016). With the wrong design a social nudge can even backfire, leading to contrary and negative behavioral effects (Bolton et al., 2018). In summary, we close this gap and aim to better understand how a social nudge design can support a better learning by triggering the use of learning strategies. Thus, we seek to answer the following research question: *How can social nudges support managing learners' self-regulation in learning to improve their learning outcomes?*

To empirically assess the potential of social nudging for this purpose, an online experiment using the between-subject A/B-testing method was conducted, and a moderated mediation model that additionally considers the effect of positive emotions was tested. With our results, we provide theoretical and practical contributions. From a theoretical perspective, we contribute to social comparison theory by presenting how socially designed digital nudges can support learners in better managing their learning process. From a practical view, we support practitioners such as managers or educators of online learning materials by guiding them to create a nudged digital learning environment.

2. Theoretical Background and Related Work

2.1 Self-Regulated Learning in Online Contexts

The focus of self-regulated learning is on learners' activity regulation, in other words, on the internal organization and structure of the learning process by themselves (Littlejohn et al., 2012). Self-regulated learning describes a self-initiated usage of cognitive learning strategies and regulatory strategies to control cognition and manage resources (Yen et al., 2018). Thus, self-regulating learners, are flexible in using learning strategies to process information as well as to monitor learning processes. Learning strategies can be described as actions, behaviors, and cognitions through which learners are trying to influence several aspects of their self-regulated learning process (Weinstein & Mayer, 1986). The use of learning strategies entails a learners sensitivity towards tasks varying initial feedback and initial conditions generated by engaging with tasks (Hadwin et al., 2001). Generally, research revealed that learners using learning strategies are more successful in online learning than the ones not using learning strategies (Daumiller & Dresel, 2019). The use of learning strategies can positively influence learners' motivation (Swafford, 2018) and different learning outcomes, e.g. achievements measured in gained points (Wadsworth et al., 2007), grades (Kuo et al., 2020), a score resulting from a knowledge test (Moos, 2013), or online assignments and exams (Broadbent & Poon, 2015). Such a self-guided regulation can be challenging to learners. Motivational problems, problems of time management, selection of appropriate learning ways and strategies, or problems with critical handling of information and learning content can occur (Sitzmann & Ely, 2011).

2.2 The Potential of Digital Social Nudges in Online Learning

Nudging is based on the assumption that a choice architecture can be used to change people's behavior in a predictable way (Thaler & Sunstein, 2008). The theoretical foundation of the concept of nudging is grounded on the dual process theory (DPT). DPT is a fundamental theory for information processing and decision making in cognitive as well as behavioral sciences. The underlying approach assumes that cognitive outcomes such as judgement, reasoning, and decision-making arise out of two mental processing systems (Grayot, 2020). There is System 1 working on a base of lower mental processing. System 1 can be characterized by fast, intuitive, automatic, affective, heuristic, and associative mental processes. Further, there is System 2 working on a base of higher mental processing, where cognitive processes are performed more controlled, reflective, rule-based, effortful, and conscious. Usually, both systems are active at the same time and interact during cognitive processing (Kahneman, 2013). However, in daily life, people often lack time and information to adequately assess situations to build their decision on systematic and reflective processing. They tend to follow mental shortcuts, such as heuristics. Therefore, it is possible to actively influence people's decision-making processes. Depending on how information is presented and framed, the outcome can be diverse (Tversky & Kahneman, 1981). The concept of nudging positions at the point that the frame of presented information is adjusted by the implementation of a nudge and by this, people's cognitive processing can be influenced. Therefore, nudges are able to push decision-making into a desired direction without forbidding any choice option (Thaler & Sunstein, 2008). In digital learning, positive effects of reminder nudges (Lawrence et al., 2019), information disclosure (Smith et al., 2018), or social nudges (O'Connell & Lang, 2018) have been reported. Even if the latter is effective in some studies, social comparison mechanisms need to be carefully integrated because social elements do not lead to positive effects in every case. In educational research, also no effects of social nudges on learning outcomes could be observed (Brown et al., 2019), and also in comparative gamified learning environments, effects vary depending on the competitive structure of social comparison (Santhanam et al., 2016). The integration of social comparison and competitive elements is challenging because depending on how these elements are designed, social elements can trigger variating effects and change outcomes.

To take up this design challenge, we have to understand the underlying mechanism of social comparison, which can be explained by social comparison theory. Social comparison theory (SCT) goes back to Festinger (1954) and states that social comparison is people's motivation to gain information about others to evaluate and assess their own performance, opinions, and abilities. This supports people in evaluating and defining themselves, improving their performances, and providing reference points in uncertain and comparative situations (Watjatrakul, 2014). Social comparison can influence various outcomes, such as individual's self-concept, level of aspiration, and feelings of well-being (Suls et al., 2002). Previous research has identified two types of social comparison, namely upward social comparison whether comparison is done with better-off others, and downward social comparison whether comparison is done with worse-off others (Latané, 1966). Upward social comparison can signal to learners that they are not as good as others are, or that there is potential to improve themselves. Downward social comparison signals learners that they are better than others, or that they might get worse in future. According to the focus on the negative or positive signals, people might feel better or worse about themselves. Thus, the emotional consequence of social comparison can differ in order to people's focus, perception, and interpretation (Bailis & Chipperfield, 2006). Especially if a situation provokes upward comparison, people see others' behavior as a desirable reference point or an existing norm, and they tend to adapt their behavior to others. Also, people care about how they are perceived by others, and therefore they feel under pressure to behave like others might expect from them. Thus, they perform expected behavior to fit into the existing social norm (Damgaard & Nielsen, 2018).

3. Hypotheses Development

Self-regulated learning processes can generally be seen in three phases that learners are going through, namely planning the learning process before learning, implementation of the plan during learning, and evaluation of the outcomes after learning (Pintrich, 1995; Zimmerman, 2000). Self-regulating learning by referring to use learning strategies is central to learn effectively (Hadwin & Winne, 1996) and finds support by research (Azevedo & Cromley, 2004; Broadbent & Poon, 2015). Such positive effects on learning outcomes result because in general, learning strategies provide guidance to learners. Learning strategies can help learners to plan, monitor, and evaluate their learning process, to self-regulate themselves in every phase.. Summarizing, we hypothesize: *H1: The use of learning strategies positively influences learning outcomes.*

According to DPT, the use of learning strategies requires information processing in System 2, but this would take learners more mental effort and time (Grayot, 2020; Kahneman, 2013) – time learners often do not have or are not willing to invest. Consequently, learners process information in their System 1 to avoid effort. Thus, they are likely to make a decision against the use of learning strategies because this is less effortful and time-consuming. As we assume self-regulated learning behavior to be more beneficial for learners, a decision against the use of learning strategies would be a decision against self-regulated learning behavior and therefore against our investigation's intentions. Consequently, digital nudges can be used at the decision point to change the informational frame. Specific nudge design and triggered underlying mechanisms can push learners to decide in favor of using learning strategies. Digital nudges address heuristics and biases, which learners tend to follow intuitively. System 1 will still be used for information processing according to DPT, but because of a controlled informational frame change now the decision is guided towards the use of learning strategies. More specifically, social nudges can be implemented to achieve this change. According to SCT, social nudges can be designed to trigger intuitive social comparison and the wish to successfully compete with peer learners. We suppose that the underlying mechanisms of social nudges push learners to the use of learning strategies even if this decision will take effort of them. Grounded on the SCT, social nudges should include upward social comparison to trigger assimilation behavior (Buunk et al., 1990; Latané, 1966). The use of learning strategies is set as the desirable behavior and simulate an existing norm that decides in favor of self-regulated learning behavior as a reference point. Learners tend to compare themselves with others and adapt their behavior to them, even if this behavior might be more effortful. Consequently, we establish the following hypothesis: *H2: Social nudges increase learners' use of learning strategies.*

Research supports our thoughts about the positive effects of social nudges on expected behaviors and decision-making in learning contexts (O'Connell & Lang, 2018). An internal resource learning strategy that is grounded on self-control and motivation is the learner's attention management strategy, e.g. a learning strategy to control thoughts to not wander away (Gravill & Compeau, 2008). At this point, social nudging can be used to trigger learners' attention to assist them in focusing on what they are doing and to select the best option for their learning. With the implementation of social nudges, we address a direct decision in favor of specific learning strategies, but there might be other learner specific learning strategies which learners are using while learning independently from the provided ones, because they might have already distinct self-regulating abilities or reliable learning techniques. Triggering learning strategies by working with nudges does not only support regulating the use of learning strategies, but it also assists learners in focusing on their activities and motivates them to keep going and to achieve the same results (or even better ones) than other learners. Hence working with social nudges amplifies the impact on learning outcomes by assisting learning in using learning strategies. Concluding, we can assume that the relationship between social nudges and learning outcomes is interrupted by the use of learning strategies. In other words, such a relationship demonstrates a mediation of an independent variable on a dependent variable which is interrupted by a mediator variable (Urban & Mayerl, 2018). Therefore, we hypothesize: *H3: The use of learning strategies mediates the positive effect of social nudges on learning outcomes.*

Emotional and cognitive processes are strongly connected in digital learning processes and both play a central role for learning (Mayer, 2019). Also, the understanding of the DPT supports the assumption, that emotions influence cognitive information processing (cf. System 1). So far, emotional responses toward digital nudges have not been deeply analyzed in research (Rela, 2022). Emotions are complex psychological constructs and can occur due to individual's evaluation of internal and external stimuli (Shuman & Scherer, 2014). Even if the relevance of emotions for learning processes is undisputed, previous research has shown inconsistent findings about the effects of emotions on cognitive processes such as learning processes. Some studies revealed positive effects of positive emotions, or negative effects of negative emotions respectively (Isen et al., 1987). But also, negative effects of positive emotions and positive effects of negative emotions on cognitive processes could be found in the past (Seibert & Ellis, 1991). Consequently, there are two contrasting hypotheses about the effects of emotions on learning: emotions-as-facilitator-of-learning hypothesis and emotions-as-suppressor-of-learning hypothesis (Park et al., 2015). Theoretically, the emotions-as-facilitator-of-learning hypothesis can be explained, for example, by the motivation-assumption where emotions facilitate learners' motivation and interest, and this supports learning processes. Especially for positive emotions, several studies proved this relation. The emotions-as-suppressor-of-learning hypothesis can be theoretically based, for example, on the extraneous-load assumption which is grounded on cognitive load theory (Um et al., 2012).

In digital learning contexts, positive emotions can have positive effects on the use of learning strategies (Marchand & Gutierrez, 2012) and self-regulated learning (You & Kang, 2014). Learners with positive emotional characteristics and profiles are more successful in learning (Wortha et al., 2019). By considering previous research, it becomes apparent that positive emotions have multiple learning-facilitating effects in digital learning contexts, whereas negative emotions can more often suppress digital learning. Consequently, we understand positive emotions as learning-facilitating, namely as a variable to positively impact learning processes by further strengthen self-regulation in learning Looking at the role of digital social nudges in online learning, social comparison can be connected with emotions. Depending on learners' focus, perception, and interpretation, emotional states can be influenced. Comparison processes where the contrast with better counterparts is dominant, learners might tend to experience negative emotions, whereas assimilation processes with better learners can lead to more positive emotions (Bailis & Chipperfield, 2006; Buunk et al., 1990). Concluding, we hypothesize: *H4: Positive emotions moderate the effect of social nudges on learning outcomes through the use of learning strategies, in the way that high positive emotions even strengthen the mediation effect.*

Summarizing our hypotheses, our research model is visualized in Figure 1.

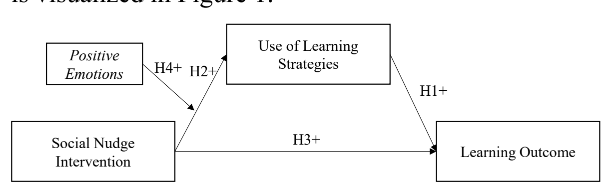

Figure 1. Research model.

4. Methodology

4.1. Experimental Procedure

To test our moderated mediation model, our study was designed as an online intersubjective A/B test experiment. Figure 2 displays the study's structure.

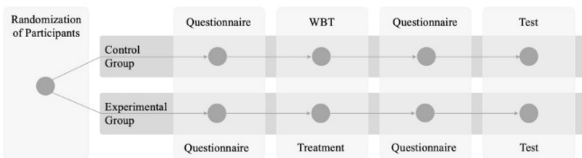

Figure 2. Experimental procedure and study structure.

The experimental setting was embedded into a web-based training (WBT) for adults on German traffic laws and rules. Subjects were offered to refresh their knowledge and to check if they would still pass the theoretical driving test in Germany. There were no further requirements except owning a driver license for at least 2 years to be allowed to participate in the online experiment. Participants were recruited via social media, authors' personal environment and social (professional) networks. Subjects were randomly assigned to one of two groups: (1) the control group that received the WBT without nudges, and (2) a treatment group where digital social nudges were implemented as manipulation. In the experiment, all subjects completed a questionnaire before and after the WBT – a test prior to the training to check their prior knowledge and a post survey to check for their success in learning based on our training. In the end of the experiment, participants took part in a knowledge test to measure learning outcomes. Test results were displayed to participants right after they ended the test.

4.2 Design of Experimental Manipulation

For this investigation we used a self-developed WBT. We generated the training's content from a lecture book (Fengler, 2010) and the "iTheorie" app (Swift Management AG, 2020). The WBT was divided into four learning sequences, participants had the option to skip sequences and also to end the WBT at any time. We included multiple supportive features in each training sequence. Supportive features were implemented as offered extensions in the WBT to use learning strategies. Previous research has already used this approach of offering supportive features to provide the use of learning strategies (Yen et al., 2018). Table 1 illustrates examples of our implemented features and underlying strategies. All learning strategies we used are based on Pintrich (1995), Weinstein and Mayer (1986), Zimmerman (2000).

Table 1. Supportive features in the WBT.

Learning Strategy	Implementation as a Supportive Feature in the WBT
Elaboration	Presenting concrete examples; instruction to connect given information with personal experiences and own behavior
Critical thinking	Instruction to reflect given information, and own knowledge and think up further solutions
Monitoring	Providing tasks and exercises to control learning progress

Our supportive features to use learning strategies were accessible by clicking a button. It was the learners' own choice to click on these buttons. Right next to these integrated buttons, social nudges appeared in the treatment group to push learners towards learning-facilitating behavior and the use of supportive features. Grounded on SCT, social nudges that use upward assimilation comparison are more effective than upward contrasting comparison. Also, research about social nudges in educational contexts has found that social comparison is more effective if comparison is done with peer behavior rather than with performance (Damgaard & Nielsen, 2018). Consequently, we used upward assimilative social comparison to compare learner's behavior. Figure 3 provides an example for the integrated social nudges.

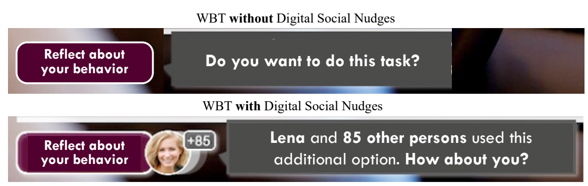

Figure 3. Digital social nudge design.

4.3. Measurement Instruments and Sample

To display the independent variable of having a social nudge in the WBT or not, we created a dummy variable with two characteristics. As learning outcome, we measured declarative domain knowledge with a detailed knowledge test consisting of 30 multiple-choice questions abstracted from original theoretical driver tests in Germany. Participants could achieve a test score up to 92 points. To examine the frequency participants clicked on the integrated buttons to use learning strategies and to conclude if participants were more likely to click these buttons when social nudges are implemented, we assess the use of learning strategies directly after participants completed the WBT (Item: "Please estimate your use of supportive functions in average: How often did you use buttons to access additional information, explanations, tasks, or examples?"). We applied a 6-point-Likert-scale (1 = never to 6 = always). In our investigation, we used the positive emotion dimension of the PANAVA-KS

(Schallberger, 2005) to measure positive emotional state consisting of four bipolar items (Cronbach's α = .868). To test our hypotheses, we performed a mediation and moderated mediation analysis. Therefore, we used the PROCESS macro for SPSS. This SPSS macro assists the estimation of the indirect effect of the independent variable, here social nudges, on our dependent variable learning outcome, by integrating a normal theory approach (i.e. Sobel test), a bootstrap approach to receive confidence intervals, and a stepwise approach to estimate the indirect effect (Baron & Kenny, 1986). The interactional influence of positive emotional state and social nudge on the use of learning strategies was used to test the moderation effect of positive emotions on the social nudge and use of learning strategies relationship. At this, the PROCESS macro facilitates testing the significance of the conditional indirect effect on different values of the moderator in the context of the mediation. To interpret the moderation effect of positive emotions we used the standard procedure to plot simple slopes of our moderation effect at one standard deviation above and one standard deviation below the moderator's mean value (Aiken et al., 1991).A total of 226 participants completed the online experiment: 108 participants in the control group, 118 participants in the experimental group. In this online experiment, participants' average age is about 30 years (M = 29.63; SD = 10.46; Med = 26; min = 20; max = 64). Out of all participants, 65.93% are female and 34.07% male. In general, the sample shows a higher educational background, 41.15% of participants have completed a bachelor's degree. Most participants are university students (61.95%), followed by employees (31.42%). In our control group, participants had 11.17 years of owning a driver license, in the experimental group we had 12.19 years of experience.

5. Results

5.1 Manipulation Check and Group Comparison

Before participants did the WBT, we evaluated whether their prior domain knowledge did significantly differ from each other to preclude group related prior knowledge biases in learning outcomes. Therefore, we conducted a corresponding Mann-Whitney-U test that did not turn out significant (p > .05), which means that there is no significant difference between the two groups regarding their prior domain knowledge. Moreover, we checked if participants in the treatment group felt more compelled to click the buttons because of social comparison. Regression analysis of injunctive norm (perceiving that other people think I should also click the button) on the use of learning strategies (the frequency participants clicked on the buttons) in the treatment group turned significant (β = .374; p < .001), whereas for the same regression model in the control no statistical evidence could be found (p = .163). We conducted further group comparison tests to check if digital social nudges achieved desired positive effects on the variables use of learning strategies and test score in the sense that the treatment group clicked on the button to use learning strategies more frequently than the control group did and also that they achieved higher test scores. Both corresponding Mann-Whitney-U tests turned out significant, which means that there is a significant difference between the two groups regarding their use of learning strategies (ULS; U = 4618.50; p < .001) and their test score (TS; U = 4027.00; p < .001). Participants in the treatment group demonstrate higher ULS (Med = 3) than participants in the control group (Med = 2). Moreover, participants in the treatment group demonstrate higher TS (Med = 80) than participants in the control group (Med = 75; see Table 2).

Table 2: Descriptive Statistics and Group Comparison

Variable		*Total*	*Control Group*	*Exp. Group*	*p-Value*
PK	*M* (*SD*)	13.21 (1.88)	13.35 (1.85)	13.08 (1.91)	.318
	Med	14.00	14.00	13.00	
ULS	*M* (*SD*)	2.88 (1.70)	2.41 (1.41)	3.32 (1.82)	< .001
	Med	2.00	2.00	3.00	
TS	*M* (*SD*)	76.70 (8.85)	73.62 (9.17)	79.53 (7.55)	< .001
	Med	78.00	75.00	80.00	

PK = Prior Domain Knowledge, ULS = Use of Learning Strategies, TS = Test Score

5.2 Mediation Model Evaluation

As shown in Table 3 there is a significant mediation effect of ULS on TS (β = .441; p < .001), and a significant effect of SN on ULS (β = .539; p < .001). Moreover, an independent linear regression analysis for the relation of ULS and TS revealed significant results (R^2 = .246; F[1] = 74.445; p < .001). Also, we find statistical evidence for the relation of SN and ULS with another independent linear regression analysis (R^2 = .069; F[1] = 17.616; p < .001). Consequently, *H1* and *H2* are supported. The results of our linear regression analyses are illustrated in Table 4. In the mediation analysis, the multiple regression model of SN and ULS on TS turns out significant (R^2 = .292; p < .001). Furthermore, the total effect of SN on TS is significant (β = .667, p < .001), the direct effect of SN on TS as well (β = .429, p < .001). As the direct effect of SN on TS is not zero, there is no total mediation. To test if there is a partial mediation, the indirect effect of SN via ULS on TS needs to turn out significant. We find a significant indirect effect because the confidence interval does not contain zero (*CL* = [1,045; 3.346]) and a Sobel test turns out significant, too (β = .238, p < .001). This means that there is a partial mediation of ULS on the effect of SN and TS, and we can support *H3*.

Table 3. Regression results of mediation.

Direct and total effects	*b*	*β*	*SE*	*t*	*p-value*
SN → ULS (a)	.915	.539	.216	4.665	< .001
ULS → TS (b)	2.304	.441	.293	7.851	< .001
SN → TS (c)	3.798	.429	1.049	3.620	< .001
SN → TS, controlling for ULS (c')	5.905	.667	1.128	5.236	< .001
Indirect effect (Sobel test)	*Estimate*	*β*	*SE*	*Z*	*p*
SN → ULS → TS (a x b)	2.107	.238	.570	3.698	< .001
Bootstrapping results for indirect effects	*Estimate*	*β*	*SE*	*95% CL*	-
SN → ULS → TS (a x b)	2.107	.238	.590	(1.045; 3.346)	-
A heteroscedasticity consistent SE and covariance matrix estimator was used (Davidson-McKinnon); Bootstrap sample size = 10000.					

Table 4. Results of linear regression analysis.

Predictors	*R2*	*b*	*β*	*p-value*	*DB*	*VIF*
ULS→TS	.246	2.606	.499	< .001	1.957	1.000
SN→ULS	.069	.915	.270	< .001	1.615	1.000
DB = Durbin-Watson-Statistic is displayed for testing requirements of no autocorrelation; VIF-values are displayed for testing requirements of no multicollinearity.						

In the mediation analysis, the multiple regression model of SN and ULS on TS turns out significant (R^2 = .292; p < .001). Furthermore, the total effect of SN on TS is significant (β = .667, p < .001), the direct effect of SN on TS as well (β = .429, p < .001). As the direct effect of SN on TS is not zero, there is no total mediation. To test if there is a partial mediation, the indirect effect of SN via ULS on TS needs to turn out significant. We find a significant indirect effect because the confidence interval does not contain zero (*CL* = [1,045; 3.346]) and a Sobel test turns out significant, too (β = .238, p < .001). This means that there is a partial mediation of ULS on the effect of SN and TS, and we can support *H3*.

5.3 Moderated Mediation Model Evaluation

The results in Table 5 demonstrate that positive emotions interact with SN to affect ULS (b = .446, p = .013; R^2 = .020, p = .013). Based on the positive interaction, we assume that the effect of SN on ULS becomes stronger with increasing positive emotions.

Table 5. Results of moderation analysis of positive emotions.

Use of Learning Strategies (ULS)						
Predictors	*R2*	*F*	*b*	*SE*	*t*	*p-value*
RM:	.275	31.495	-	-	-	<.001
SN	-	-	-1.142	0.696	-1.164	.102
PA	-	-	-.054	.305	-.177	.860
SN x PA	.020	6.255	.446	.178	2.501	.013
A heteroscedasticity consistent SE and covariance matrix estimator was used (Davidson-McKinnon); Unstandardized regression coefficients are reported.						

Table 6. Conditional indirect effects of social nudges via ULS on test score.

Positive Emotions		*Effect*	*SE*	*CL*
One *SD* below	2.931	.381	.567	(-.694; 1.544)
Mean	4.048	1.529	.519	(.596; 2.633)
One *SD* above	5.164	2.676	.818	(1.178; 4.408)
A heteroscedasticity consistent SE and covariance matrix estimator was used (Davidson-McKinnon); Bootstrap sample size = 10000.				

To illustrate the interaction, we plot simple slopes. Table 6 visualizes the simple slops and supports our assumed relation. Only the simple slop test for high level of positive emotion becomes significant (*CL* = [1.178; 4.408]).

6. Discussion and Contribution

The goal of our study was to understand how social nudges can support a self-regulated learning aiming to achieve better learning outcomes (RQ). Learning strategies are a central element of self-regulated learning behavior which positively affects learning processes (Broadbent & Poon, 2015). Learning shifts away from instructor-driven classroom learning, and therefore theory and research need to adapt to address the role of self-regulation (Sitzmann & Ely, 2011). Therefore, in our study, we decided to focus on the use of learning strategies and the effect of social nudges to better guide learners in self-regulation. Learning strategies matter because, there is a great importance in exploring and embedding new features and functions in online learning environments to support learners in self-regulating their learning process. Such functionalities are represented by digital nudges. Especially exploring social nudges is of relevance for research because with the wrong design, they can lead to contrary effects (Bolton et al., 2018). As our findings reveal, supportive features to use learning strategies positively impact the actual use of learning strategies and further increases learning outcomes (*H1*). Moreover, the results of our study highlight, that using social comparison – instantiated by social nudges – is a supportive instrument to assist learners in deciding for supportive functions (*H2*) and fulfilling learning outcomes (*H3*). SCT says that individuals compare themselves with others in order to examine opinions, to judge, and to decrease uncertainty (Festinger, 1954). Comparing themselves makes individuals aware of their level of skills, abilities, status, or position relative to others, and it encourages competition (Garcia et al., 2006). Individuals compare themselves with others when they need to rely on an external standard against which to judge themselves (Li et al., 2015). Instead of letting them compare their progress like a ranking, we use social comparison as a guiding nudge. Once regulating the own learning process, learners are fully responsible for their actions – with social comparison they are indirectly assisted by others which can make learning easier. Referring to the context of digital learning and the implementation of nudges, SCT posits that learners require information to evaluate their options and abilities (Festinger, 1954) – thus being guided when operating in an online training. Consequently, social nudges that provide guidance, can support this need. Being guided in such a way is especially of relevance because self-regulating a learning process is often challenging to learners and not easy to handle (Gravill & Compeau, 2008). For our study, we referred to upward assimilative social comparison.. In digital learning environments it is important to support learners in focusing on what they are doing to keep them engaged in their learning process (Gupta & Bostrom, 2009). With upward social comparison, learners perceive that others are better-off and are triggered to get more active to be able to complete an online training as good as the other learners, also being capable to handle a learning process alone like others already did. But situations that allow a downward comparison could lead to negative effects in digital learning, because learners can get easily frustrated resulting in weaker learning outcomes (Santhanam et al., 2016). As a result, we can assume that an upward and assimilative social comparison is more likely to be supportive for a learner's progress. The results of *H2* and *H3* strengthen our assumption.

Another important facet of our study is the role of emotions. Positive emotions arise very often as learning facilitating and supportive for self-regulation processes in learning (Marchand & Gutierrez, 2012). Based on the emotions-as-facilitator-of-learning hypothesis (Um et al., 2012) we understand positive emotions to even strengthen learning processes and therefore, to foster learners' self-regulated learning behavior. Our findings support the theoretically assumptions by demonstrating that high level of positive affect even increase the effect on the use of learning strategies, whereas a low level of positive emotions does not have a significant influence on learners' self-regulating behavior (*H4*). Moreover, triggering the assimilative comparison with other learners by social nudges might emotionally reinforce the effectiveness on the use of learning strategies. But, supporting emotions with social comparison must be handled carefully because a more contrasting comparative design could result in negative affect such as frustration which, in turn, has a contrary effect in relation to self-regulate or succeed in learning (Pekrun et al., 2017). Our results help us to derive theoretical and practical contributions. From a theoretical perspective, we support theories about digital learning and digital nudges on how to work and use digital nudges effectively to support learners in better managing their learning processes. We enrich social comparison theory by presenting a nudge design that provides guidance in handling a complex learning process. As a result, we present a solution of how to design digital social nudges that can be integrated in a digital learning environment contributing to a positive learning behavior. From a practical perspective, we support practitioners in guiding them towards creating an effective nudge design in digital learning. Digital learning has become more important over the last month, and new innovative ways are required to better support learners in being capable of managing their own learning actions. Once we can better assist employees in better managing learning processes on their own, companies can benefit from saving costs and at the same time increasing the employee's empowerment to be capable of their own actions.

7. Limitations and Future Research

Our study has some limitations that offer room for future research. Learning environments that support learners in practicing their self-regulation abilities might help learners to internalize and automatize these abilities over time. As we only trigger behavioral changes with our manipulation, it still stays unclear if we can achieve long-term and sustainable development of competences such as self-regulated learning skills. In further research, longitudinal studies might help to elucidate this topic. Additionally, studies should further explore and analyze the processes of self-regulated learning. In such studies, the timing of the learning process and also the kind of nudge could be varied and analyzed. To investigate sustainable learning success, procedural or situational knowledge would be interesting, too. Additionally, we integrated a variety of learning strategies as supportive features from different categories, but the effect of learning strategies can variate between the type of strategy. In our investigation we measured behavior of using learning strategies by a self-assessment of learners, but the discrepancies of self-evaluation and actual behavior might influence results. Future research should address this point.

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