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The Power of Positivity: Framing IS adoption messages just right

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Short Paper

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Abstract

In a longitudinal study of differences in framing an introduction of Grammarly, we find a gain framing to be more effective. Grammarly is an online spell-checking tool that can, for example, improve the text quality of students. We used the unified theory of acceptance and use of technology UTAUT to study framing effects on adoption behavior. In a survey experiment, we presented students with a description of Grammarly that was either framed towards potential gains or potential losses use would avoid. Contrary to prior findings in the context of IS security, we find a gain framing to be more effective. We discovered, however, that the framing was only effective after three months, which offers initial insights into the effects of framing in information systems and raises new questions. We plan to study this effect further in a follow-up study with a larger number of participants.

Keywords: Framing, technology acceptance, experiment, Grammarly, students

Introduction

Research across fields has shown that message framing can influence individuals' intentions but IS researchers have not yet explored how to use framing effects to increase technology acceptance. Since Tversky and Kahneman's (1979) discovered how framing influenced individuals regarding a decision problem – in their case, either a gain or loss framing – it has been studied across research fields. IS researchers have made the first attempts to instrumentalize framing for IT security (Ayaburi and Andoh-Baidoo 2019; Goel et al. 2017; Bahreini et al. 2020; Syed 2019; Garza and Guo 2015; Samander et al. 2017). Thus, it should be possible to increase the scope of application in IS, e.g., by utilizing framing to influence participants towards an increased acceptance and use of a new system – a potentially vital aspect of digitalization. But if IS researchers and practitioners want to instrumentalize framing effects, we need clarity on which framing (gain or loss) would be more effective. The common recommendation from the literature is to communicate user benefits – thus a gain framing – in technology acceptance contexts (Kim and Kankanhalli 2009; Hsieh 2015; Zhao et al. 2016). However, a practical test by Weiler et al. (2019) found that a negative framing was more effectful in influencing participants in a choice between two decision support systems. If a gain or loss framing is more effectful, thus, remains to be tested.

Researchers typically measure technology acceptance with well-established technology acceptance models – the most prominent one in IS being the unified theory of acceptance and use of technology (UTAUT). However, to date, it is unclear how exactly framing influences technology acceptance as conceptualized by UTAUT. Intentional use of framing effects could increase technology acceptance and use, thereby increasing the value gained from IT investments for all stakeholders involved. To test the effectiveness of framing as a tool to improve technology acceptance we use a student setting with the introduction of Grammarly, an online writing assistant. We chose this scenario because we wanted to avoid the typical conundrum where researchers test business problems on students with limited transferability (Compeau et al. 2012). Therefore, we chose a technology that students could also use to write better texts, which would also actively benefit our students. For the message framing, we chose a gain and loss framing in line with prospect theory (Tversky and Kahneman 1979) and several prior studies in IS (Goel et al. 2017; Howell et al. 2016; Bahreini et al. 2020; Weiler et al. 2019). We thus focus on the research question: *Can a loss or gain framing influence the level of technology acceptance of students towards Grammarly?*

Background

UTAUT

In information systems (IS), researchers typically model technology acceptance using established technology acceptance models. Venkatesh et al. (2003) developed UTAUT by consolidating the first six models. They established that performance expectancy, effort expectancy and social influence predict the behavioral intention to use a new system. Combined with facilitating conditions behavioral intention predicts use behavior (please refer to Table 1 for definitions of all constructs). Since then, many researchers have used UTAUT to assess technology acceptance in different contexts, and to date, it is still the model most often used (Williams et al. 2015). Therefore, we will also use UTAUT in this research effort. Interesting in the context of our study is a limitations Venkatesh et al. (2008) identified: Behavioral intention cannot predict behavior outside of the individual's volitional control. A cause for such behavior could be an external influence – potentially without the individual's awareness of being influenced.

Prospect theory and framing

Tversky and Kahneman (1979) developed prospect theory based on a series of experiments where they were able to show that individuals reacted more loss averse to decision problems than utility theory would have predicted. In their experiments they tested the influence of either framing a decision problem in terms of losses or gains. They found that with a loss framing individuals reacted more risk averse and forewent potential gains. Their findings encouraged further research both into loss aversion and framing. In IS, loss aversion has garnered increased attention in the context of status quo bias and its influence on technology acceptance (Godefroid et al. 2022). Kim and Kankanhalli (2009) for example examined the effects of loss aversion as one explanation approach for status quo bias on technology acceptance. Framing, however, does not yet appear in that context. Instead the most prominent IS studies on framing effects focus on security related questions, e.g., framing feedback messages regarding security aspects of IS use (Bahreini et al. 2020)

Constructs	Definition	Source
Performance expectancy (PE)	Performance expectancy measures how far an individual perceives a new system to be helpful in their job performance.	(Venkatesh et al. 2003)
Effort expectancy (EE)	Effort expectancy measures how far the individual perceives the new system as easy to use.	
Social Influence (SI)	Social influence measures how far individuals perceive their use of the system relevant to other individuals important to them.	
Facilitating Conditions (FC)	Facilitating conditions measures how far the individual perceives the availability of infrastructures necessary for system use.	
Behavioral intention (BI)	Behavioral intention describes the behavioral intention of the individual to use the system.	
Use Behavior (UB)	Use behavior measures the actual use of the information system by the individual.	
Framing (FR)	We presented participants with a description of Grammarly that was either phrased to showcase potential gains if they used the software or potential losses if they did not use the software.	(Goel et al. 2017; Howell et al. 2016; Bahreini et al. 2020; Weiler et al. 2019)

Table 1. Constructs derived from literature

IS researchers typically translate loss aversion into the hypothesis that a loss framing should have a larger effect than a gain framing (Howell et al. 2016; Weiler et al. 2019; Goel et al. 2017; Bahreini et al. 2020). For example, Bahreini et al. (2020) proposed that participants receiving negatively framed feedback would be more likely to optimize their security settings in an app compared to novice users who received positively framed feedback. However, they found no direct effect of framing. This is in line with findings from literature that framing effectiveness is context-dependent. In healthcare, it was possible to establish a logic behind such contextual effects. For example, researchers found that a gain framing was more effective in a prevention context, while in a diagnosis context, a negative one was more effective (Rothman et al. 2005). Thus, framing could have different effects in a technology acceptance than in an IS security context.

Hypotheses

To measure technology acceptance, UTAUT is currently the most prevalent model in IS research (Venkatesh et al. 2016); therefore, we also employ it in this research and derive corresponding hypotheses.

- *H1: UTAUT also applies to the introduction of Grammarly at t=1 and t=2 (H1.1-H1.8).*

Regarding the effects of a gain or loss framing, research appears to remain divided. Two studies in the IS security and phishing context hypothesized that a negative framing would be more effective but find no effect of message framing (Goel et al. 2017; Bahreini et al. 2020). One study that assessed the likelihood of smart card adoption found evidence for the effect of a negative message framing (Howell et al. 2016) in line with more general healthcare research for a diagnosis context (Rothman et al. 2005). A study focusing on loss aversion effects on the choice between two decision support systems also found that the loss framing increased the conversion propensity (Weiler et al. 2019). However, as we study framing in the technology acceptance context, and as general technology acceptance literature typically recommends framing possible gains of the new system for users (Kim and Kankanhalli 2009; Hsieh 2015; Zhao et al. 2016), we expect a higher impact of a positive message framing. As framing showed to be highly dependent on the context in healthcare (Rothman et al. 2005), we hypothesize that the context is more relevant here.

- *H2: Positive influence of a gain framing – in contrast to a loss framing - on UTAUT constructs at t=1 and t=2 (H2.1-H2.10).*

We derived a research model (see figure 1), which we test in the following.

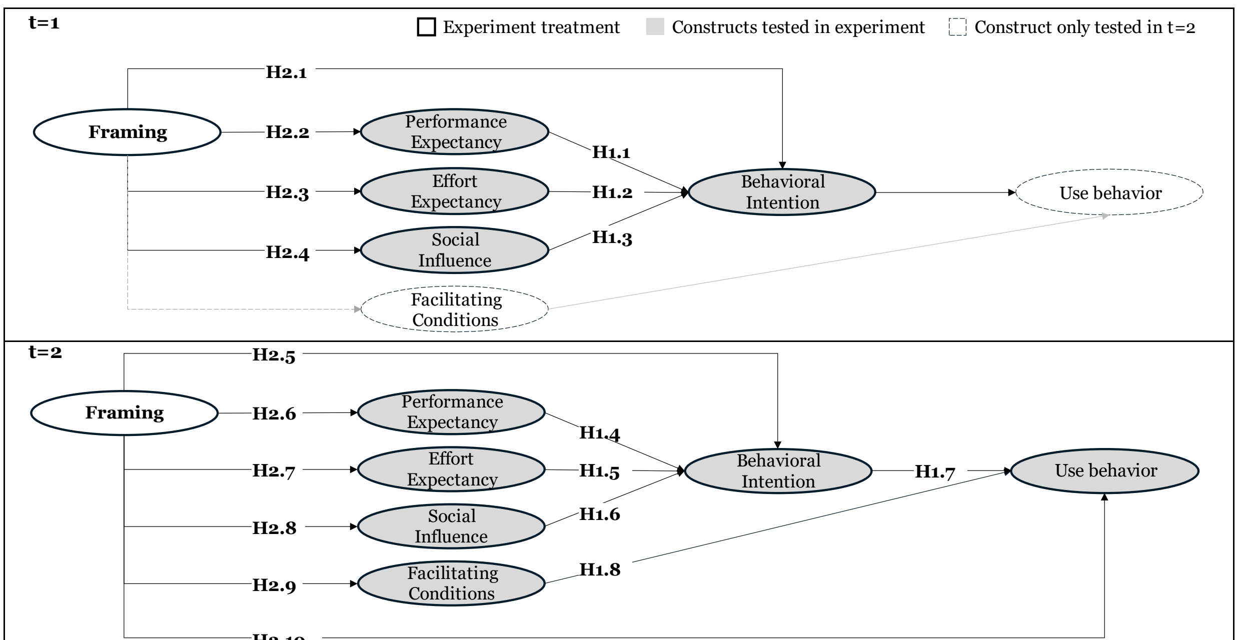

Figure 1. Research model

Research Method

To assess our hypotheses, we used a quantitative approach and employed structural equation modeling (SEM) using partial least squares (PLS) (Hair et al. 2017; Hair et al. 2019). This method is well-accepted in IS research for this type of endeavor (Petter 2018).

Case description

Grammarly is an online writing assistant available for free in the basic version. Users can access it via a browser plug-in or an online editor. For the online editor, the user has to create an account, but its use is free in the basic version. Once the author has pasted a text into the Grammarly editor, the program makes so-called suggestions regarding correctness, clarity, engagement, and delivery. A simple click can accept these suggestions, and the editor then changes the text accordingly. In the paid version of the software, additional features like grammar suggestions are available. Such online writing assistants can be helpful tools, especially for individuals who write many texts in their job or studies. They are typically able to detect more mistakes than Word spell-checking. Therefore, we can recommend these technologies to students who need to write and hand in texts for their coursework. However, as the researchers involved in teaching on undergraduate level, we know that many of our students do not use these tools (based on the text quality we receive). We resorted to recommending such tools to students to improve their writing. As a faculty, we wondered how to make this recommendation most effectful and if this might be a case of a lack of technology acceptance.

Measurement

We conducted a longitudinal study with two surveys 3 months apart. We primed participants from undergrad courses in the first survey with a gain or loss framing and then measured the effects. Based on the information on www.grammarly.com, we created two texts (see Table 2) focusing on the potential personal advantages or gains the user could achieve and the disadvantages or losses they could avoid.

Gain Framing	*Why should you use Grammarly?* *Grammarly will help you to write better and error-free texts. It alerts you to spelling and punctuation mistakes. This way you can improve the quality of your homework, assignments, reports, or even your thesis when you hand them in.* *Mistake-free texts can help people to get the right impression. A person correcting your text can concentrate on the content of your work and your texts will be easier to read. This could also affect this person's perception of you. For example, Kreiner et al. (2002) found that college students attribute spelling mistakes to writing ability, but also to logical and intellectual ability.* *During your studies, you will have to do a lot of writing. It makes sense to learn tools that can help you write better texts early. Just imagine what you would think about someone who is very good at writing texts. Do you want to be that person?*
Los Framing	*Why should you use Grammarly?* *Grammarly will help you to avoid making mistakes in your writing. It alerts you to spelling and punctuation mistakes. This way you can prevent errors from being left in homework, assignments, reports, or even your thesis when you hand them in.* *Mistakes in writing can lead people to get the wrong impression. A person correcting your text could make the involuntary inference that you made other mistakes if you make spelling mistakes. For example, Kreiner et al. (2002) found that college students attribute spelling mistakes to writing ability, but also to logical and intellectual ability.* *During your studies, you will have to do a lot of writing. It makes sense to learn tools that can help you to avoid mistakes early. Just imagine what you would think about someone who makes a lot of mistakes in their writing. Do you want to be that person?*

Table 2. Texts for the gain and loss framing

For measurement, we used the items by Venkatesh et al. (2003) to measure the UTAUT constructs performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention and usage behavior. Following prior literature, we used a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) to assess all measurement items. The actual questions used can be obtained from the authors upon reasonable request. We could only measure actual use and facilitating conditions in the follow-up survey (t=2), as these affect actual use directly (Venkatesh et al. 2003). As we focused our experiment on users that had not used Grammarly before, we could only ask these questions in the follow up survey, when they had started using the system. For all other constructs we collected two values at both points in time. Following prior literature, we used structural equation modeling (SEM) with the partial least squares (PLS) technique to analyze the hypothesized causal relationships between the constructs. PLS has been employed for UTAUT before (Venkatesh et al. 2003). Therefore, we deemed it appropriate.

Survey administration and data inspection

We administered the survey experiment via Unipark and assigned participants to the gain or loss treatment randomly. To ensure that all participants had interacted with the Grammarly editor and were thus able to give us the full assessment, we asked them to edit a short text. For this purpose, we created a version of the framed text with mistakes. We then presented these to the participants, who had already seen the text in the introduction, and asked them to correct it with Grammarly. We highlighted that we could not use submissions that participants had edited by hand. On a subsequent page, we then asked them to insert the corrected text in the survey. This correction exercise also allowed us to exclude non-valid responses. A spelling test of the submitted texts allowed us to determine if the participants had paid attention and if they had used Grammarly. We excluded answers where participants had not corrected all mistakes. This step was done to exclude inattentive respondents and thereby improve data quality (Abbey and Meloy 2017).

In total, we recruited 214 students for our research from two universities and via Prolific. All 51 university students were first year students in undergraduate programs of information systems. In addition, we recruited 163 participants via Prolific, where we focused on undergraduates from business and computer science courses – no other selection criteria were applied. The participants from Prolific were expensed for their time per the site's guidelines, no other incentives were provided, that could have distorted results. received the recommended Due to our attention check described above, we had to exclude results from 32 survey submissions. This step left us with 182 valid responses. After three months we conducted a follow up survey, which 101 individuals answered. Of these 75% were male. The average age was 22 years (min 19 - max 35 years). Our participants had varying levels of experience, while 31 had already used Grammarly before, 12 had used a writing assistant, 31 the Word spell-checking solution, and 27 participants no experience with any writing assistants at all. As we wanted to assess the effects of the introduction of Grammarly and framing would probably not have an effect on individuals already using Grammarly we had to exclude the 31 individuals that already used Grammarly from our subsequent analysis. We did not reveal the nature of the framing during the experiment, thus we could not observe any behavioral changes in reaction to that.

Measurement model analysis

We conducted all analyses using Smart PLS 3.3.3 (Ringle et al. 2015) and used thresholds in line with Hair et al. (2017). We employed three criteria for measurement quality: Firstly, we used Cronbach's alpha (Hinton 2008) to test for internal consistency reliability; secondly, we used the average variance extracted (AVE) to test for convergent reliability; thirdly, we used the Fornell–Larcker criterion to estimate discriminant validity (Fornell and Larcker 1981). We conducted one pre-test with ten other researchers and found no issues. Tests for construct reliability and validity were positive for all constructs apart from facilitating conditions (see Table 3). A deeper analysis showed problems with one item for facilitating conditions (fc03), as the factor loading was insufficient (0.175). We assume that this was due to the lightweight nature of Grammarly and deleted fc03 from the further analysis. Afterwards, the values for Cronbach's alpha were above the threshold of 0.7 (Hinton 2008) – again apart from facilitating conditions. As this is, however, a construct that has worked in numerous other contexts we decided to keep it to ensure content validity (Hair et al. 2017). The correlations between all constructs were lower than the square root of the AVE, which supports convergent and discriminant validity (Fornell and Larcker 1981). A look at the level of the factor loadings (see Table 4) revealed that at t=1 ee02, ee02, and ee03 were slightly below the threshold of 0.7. As we adapted this construct from prior literature, we decided to keep the item to ensure content validity. Also the follow-up survey at t=2 showed no such issues. For facilitating conditions, fc04 was slightly below the threshold of 0.7. As Grammarly provides support upon request, we decided to keep this item to ensure content validity following the suggestions of Hair et al. (2017).

		Cronbach's alpha	AVE	PE	EE	SI	BI	FC	UB	FR
t=1	**PE**	.870	.720							
	EE	.822	.654	.333						
	SI	.926	.871	.343	.130					
	BI	.980	.962	.788	.356	.392				
	FR	1.0	1.0	.188	.089	.033	.193			1.0
t=2	**PE**	.878	.732	.870						
	EE	.873	.718	.506	.867					
	SI	.829	.736	.400	.298	.899				
	BI	.964	.934	.776	.473	.313	.975			
	FC	.506	.498	.482	.568	.374	.408	.706		
	UB	.670	.596	.547	.387	.008	.684	.360	.782	
	FR	1.0	1.0	.017	.065	-.174	.108	.048	.223	1.0

Table 3. Construct reliability and discriminant validity

In addition, we conducted Harman's single factor test to check for common method bias using SPSS. For both measurement points our result was well below 50% of variance explained by a single factor (Podsakoff et al. 2003). For the model at t=1 the variance explained by a single factor was 43,3% and for the model at t=1 it was 34,5%. Thus, we assume that common method bias did not significantly distort our results.

	Construct	Item	Loading	Construct	Item	Loading
t=1	Performance expectancy (PE)	pe01	.930	Social influence (SI)	si01	.935
		pe02	.741		si02	.935
		pe03	.777		si03	.933
		pe04	.803	Behavioral intention (BI)	bi01	.941
	Effort expectancy (EE)	ee01	.627		bi02	.999
		ee02	.690		bi03	.929
		ee03	.936	Framing (FR)	fr01	1.0
		ee04	.567			
t=2	Performance expectancy (PE)	pe01	.851	Facilitating conditions (FC)	fc01	.711
		pe02	.893		fc02	.712
		pe03	.874		fc04	.662
		pe04	.861	Behavioral intention (BI)	bi01	.981
	Effort expectancy (EE)	ee01	.895		bi02	.963
		ee02	.781		bi03	.981
		ee03	.881	Use Behavior (UB)	ub01	.711
		ee04	.908		ub02	.702
	Social influence (SI)	si01	.910		ub03	.914
		si02	.919	Framing (FR	fr01	1.0
		si03	.866			

Table 4. Factor loadings

Structural model analysis

We ran both the general PLS algorithm and the bootstrapping variant to assess our model. For the parameters of the PLS algorithm, we followed Hair et al. (2007) and the agreed-upon standards. We used a path weighting scheme with 300 iterations and a stop criterion of 10-7. To test the significances of our model, we employed bootstrapping using 5,000 iterations of randomly drawn subsamples and the parameters as indicated above (Hair et al. 2017). As a result, we identified two significant influences of our treatment (see Figure 3), which we present in the following according to our hypotheses.

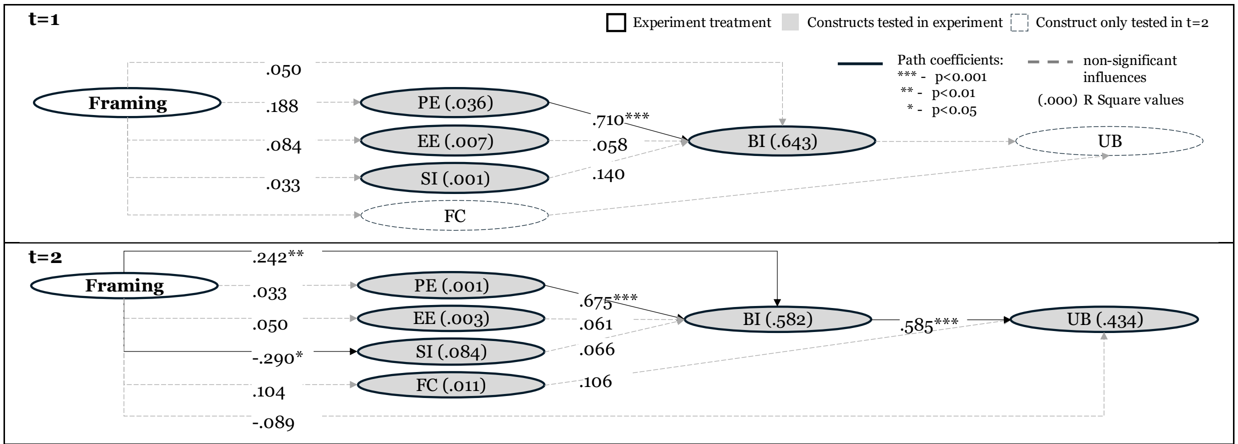

Figure 3. Results of PLS-SEM analysis

Table 4 presents the path coefficients we assessed to test our hypotheses. We hereby analyzed significance based on the p-values of the path coefficients (*** = p-value <.001, ** = p-value <.01, *** = p-value <.05). Our data provide partial support for H1. We see strong effects of performance expectancy on behavioral intention (H1.1+). We expected all constructs to work well as UTAUT is well established and studied countless times across different contexts (Venkatesh et al. 2012). However, counter to that expectation, we did not observe significant effects of social influence and effort expectancy on behavioral intention (H1.2-, H1.3-). This effect might be due to Grammarly being an easy to us online tool. So, the user does not need to install any software and only to create an account. Therefore, the perception of the effort might not have significantly influenced the participants' intention to use Grammarly. Similarly, spelling mistakes potentially should be a focus of student conversations, but apparently not much social pressure applies to a choice of spell-checking tool. Which would explain the lack of significance of social influence. Regarding the effects of the gain or loss framing, we saw no significant effects; therefore, we must reject H2 at t=1 (see Table 5). This result was contrary to our expectations from prior literature.

		PE	p-value	EE	p-value	SI	p-value	BI	p-value	FC	p-value	UB	p-value
t=1	**PE**							.710	.000				
	EE							.058	.654				
	SI							.140	.159				
	FR	.188	.145	.084	.694	.033	.865	.050	.0541				
t=2	**PE**							.675	.000				
	EE							.061	.444				
	SI							.066	.481				
	BI											.585	.000
	FC											.112	.316
	FR	.033	.789	.050	.714	-.290	.020	.242	.004	.104	.489	.089	.285

Table 5. Path coefficients (* = p-value <.001, ** = p-value <.01, *** = p-value <.05).**

At t=2 we found the same picture regarding the direct determinants of UTAUT – only performance expectancy had a significant effect (H1.4+, H1.5-, H1.6-). Facilitating conditions also had no significant effect on use behavior (H1.7-). A potential reason being that Grammarly does not need any expert support and the basic version is free. However, we did find a significant effect of our framing on behavioral intention (H2.5+). In addition, we found a weaker effect of our framing on social influence (H2.8+). But as social influence did not affect behavioral intention, we dismiss this finding in our further discussion. Framing did not affect any other of the constructs (H2.6-, H2.7-, H2.9-, H2.10-). This effect is interesting as the framing did not affect behavioral intention at t=1. Thus, it apparently took some time for our framing to take effect.

Discussion

In our longitudinal study of framing a Grammarly introduction for students, we found that a gain framing had more effect than a loss framing – but only after three months. This phenomenon requires further study, however, in line with prior theory we can hypothesize two explanation approaches: It could be that framing effects simply take time. We still know very little about how exactly cognitive biases work in IS and if they potentially have time delayed effects (Godefroid et al. 2021). The other explanation could be that framing is exactly one of those influential factors outside of the individual's volitional control that Venkatesh et al. (2008) describe. It would explain that behavioral intention at t=1 was not affected because the intention remained unaffected, while their (subconscious) actual behavior had already shifted. To solve this conundrum, we plan to conduct a follow up study with a larger number of participants to ensure sufficient numbers in a follow-up survey. In this study we want to explore three key aspects: 1) The nature of framing, i.e., explore the effect of other frames and the amount of framing necessary; 2) the nature of time lag, i.e., follow-up after 3 days, 3 weeks and 3 months; and 3) the effects of the measurement model, i.e., we also want to include the complementary concept of behavioral expectation to further our understanding of framing effects on behavioral intention (Venkatesh et al. 2008).

Our findings are still preliminary due to the low number of participants that answered to our second survey, but they hold important contributions for theory and practice. We conducted one of the first longitudinal framing studies in IS. This method allowed us to gain more in-depth insights into the actual effects of framing. Time delayed effects already appear in technology acceptance literature e.g., Venkatesh et al. (2003) measured user reactions at introduction and after 3 months. Future studies will have to explore the exact temporary effects in more detail. We also contribute to the existing knowledge on frames in IS, as we found a gain framing to be more effective - in contrast to the smart card adoption context Howell et al. (2016) examined. This contrast indicates that similar to the findings from healthcare also in IS the most effective framing is highly dependent on the exact context (Rothman et al. 2005). For practitioners our findings have the implication that when introducing new systems, the focus should be on potential benefits and not on losses or risks prevented. Such a framing can aid adoption as we saw significant effects from only showing participants a small text. Potentially framing the complete communication material for a system introduction could have even stronger effects.

Even though we took the outmost care to design our research, there are some limitations, which we believe however, rather offer opportunities for further research. Firstly, the sample size of 70 individuals that filled out the second survey and had the right experience level is surely too small. It can, however, offer a strong indication and we plan to conduct a follow up study examining these effects in more detail. Secondly, we focused our scenario on Grammarly and students to create a realistic introduction scenario, this led to issues with certain constructs form UTAUT. Future studies might test the applicability of our findings for other technologies for which the UTAUT constructs have been shown to work well. In addition, other potential factors e.g., text size and complexity in the context of Grammarly require further attention. Also framing on the single recommendation level should be evaluated. Thirdly, we relied only on self-reported measures. Thus, we cannot dismiss the possibility that results were biased (Podsakoff and Organ 1986). We conducted a Harman's single factor test to mitigate this risk. Future studies could avoid this issue by including actual evidence of use behavior e.g., system logs. We hope that our work also inspires others to study cognitive biases in IS and technology adoption even further.

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