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Digital Nudges in Enactive End-User Training

By

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Management Sciences

(User Experience in a Business Context)

Under the direction of

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CERTIFICAT D'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

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Further to the evaluation of your Form F8 – Project Modification, the Research Ethics Board (REB) of HEC Montréal wishes to inform you of its decision:

The changes have been noted in the file. The current certificate will remain valid until the next renewal.

Thank you.

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Abstract

Enterprise Systems (ES) have become a cornerstone in today's business landscape. However, the success of ES implementations largely on its end-users having the requisite knowledge and skills to use the ES effectively. Serious business simulations are a relatively recent methodology of teaching ES concepts to employees. Business simulations have the benefit of increasing learner engagement, but with the tradeoff of higher cognitive load. Consequently, this could have a negative impact on learning effectiveness. Recently, nudging has garnered interest in the Information Systems (IS) and education fields as tools to help learners. Nudges are non-intrusive, gentle pushes that aim to steer behaviour. For example, warning labels on cigarette packages are a type of nudge. This thesis by articles studies the interaction between the learner and business simulations, and investigates the viability of 2 types of digital nudges, warning and social nudges, in increasing learning effectiveness in an enactive end-user training context.

Following a systematic literature review, we hypothesize that in an enactive problem-solving context, social and warning nudges would be beneficial to learning outcomes. Additionally, we also hypothesize that social nudges would have a greater impact than warning nudges, and that individual characteristics such as prior ES experience and self-efficacy affects the effectiveness of either nudges. To test our hypotheses, a between-subjects was conducted remotely with 64 participants where they played an ERPsim game. We compared learning outcomes between 2 treatment groups (social nudge, warning nudge) and a control group.

Our results indicate that simple digital nudges may not be enough to significantly help learners in a complex enactive end-user training scenario. However, results also indicate that experts and novices, as well as participants with a high versus low self-efficacy, respond differently to the type of nudge. Notably, novices and low self-efficacious individuals prefer more directed nudges and respond better to the social nudge, whereas experts and high self-efficacious individuals are not adversely affected by warnings and respond better to the warning nudge. This thesis therefore contributes theoretically by answering calls to further research digital nudging, and practically by outlining design recommendations for nudge designers and educators.

Keywords: Enterprise Systems, End-User Training, Nudge, ERPsim, Learning

Table of Contents

List of Figures and Tables

The numbering of figures and tables have been modified in the articles to facilitate the reading of this thesis.

List of Tables

List of Figures

Preface

With the authorization of the Academics Affairs Office of the Master of Science in Management program, this thesis in User Experience in a Business Context is written in English and in the form of two articles.

The first article takes the form of a systematic literature review. It outlines research objectives, the current state of research of the topic in the thesis and research opportunities. This article was submitted to the AMCIS 2021 proceedings in March 2021.

The second article is a scientific article reporting the results of the experiment conducted over the summer of 2020 and is in preparation for submission to the *Journal of Computer Information Systems* (JCIS).

All articles presented in this thesis were co-authored and were added to the thesis with their signed consent.

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Chapter 1

Introduction

1.1 Context

Companies have been replacing their legacy systems with enterprise systems (ES) since the 1990s. Enterprise Systems have become ubiquitous and form the backbone of most large firms (Samara, 2015). Enterprise systems dismantle silos of information, integrate business processes and allow for the efficient and effective use of resources within firms (Nah, Lau & Kuang, 2011). It is not difficult to imagine the benefits of having an ES within larger firms, considering the sheer amount of business processes that can span across regions or countries. The market for ES remains anything but stagnant. Gartner forecasts that ERPs alone will be worth $44 billion by 2022 (Torii, 2020).

However, implementing ES is not an easy task. Failure rates for ES ventures are surprisingly high; research has come up with failure rates from anywhere to 50% to a staggering 84%, depending on the failure criteria used in the evaluation (Saxena, Dempsey & McDonagh, 2016). A major factor for implementation failure is lack of training, or even ineffective training programs (Rajan and Baral, 2015). As such, firms are investing considerable amounts of money into end-user training (EUT) in order to increase the likelihood of user acceptance of the new ES. To put this into perspective, U.S companies spent $109.25 billion in 2005 on training programs (Gupta, Bostrom & Huber, 2010). However, returns on investment in EUT are generally low, as employees often do not apply these newly learned skills in their jobs (Glaveski, 2019).

New methods of EUT are gaining in popularity, such as serious games for learning (Hallinger & Wang, 2020). Serious games have educational purposes and provide an enactive method of learning where players can develop their competencies and skills by doing. They offer an environment where students can safely experiment and learn from their decisions and mistakes (Léger et al., 2011). Serious games have been shown to induce higher cognitive engagement when compared with non-game-based learning, thereby enhancing learning (Zhonggen, 2019). Therefore, they can offer a more effective learning experience to employees.

However, serious games also have their downsides. While they induce higher engagement within learners, they also result in higher cognitive load, which can negatively impact learning effectiveness (Zhonggen, 2019). Higher cognitive load also makes learners more susceptible to cognitive biases, systematic errors that occur when heuristics are used (Schwenk, 1986; Kahneman, 2011). Heuristics are strategies used to simplify the task when the optimal solution is too computationally complex for the human mind to handle (Gigerenzer, Hertwig & Pachur, 2011).

In light of these cognitive biases, two American scholars, Thaler and Sunstein (2009) coined the term “nudge”, which are interventions aiming to influence behaviour without restricting freedom of choice. These nudges seek to leverage or combat these cognitive biases in order to steer behaviour towards a desired direction. Nudges can either influence behaviour unconsciously or engage reflective thinking (Münscher, Vetter & Scheuerle., 2016). An example of an unconscious nudge is reducing the size of dinner plates, which results in people consuming less calories on average (Hansen & Jespersen, 2013). “Reflective” nudges, on the other hand, require the recipient’s collaboration in order for the nudge to work; for example, warning users may make them more cautious and therefore consider a larger amount of information before making a decision (Raschke & Steinbart, 2008).

1.2 Research Objectives

EUT outcomes can include many elements. Gupta et al. (2010) describe 4 different training outcomes based on a literature review, which can be found in Table 1. For the purposes of this study and to reduce the scope of the experiment, we choose to focus on skill-based goals (trainee’s ability to use the target system) and affective goals (attitudinal goals, such as confidence, motivation, etc.). The ability to use a system is arguably the most important outcome of EUT, but affective goals can be equally as important. Studies have shown that employees with higher self-confidence and motivation will invest more effort and learn more effectively (Utesch et al., 2016; Bernard & Senjaywati, 2019; Kazimoglu, 2020). In this study, we specifically refer to an enactive EUT context. Enactive learning refers to learning from the consequences of one’s actions and feedback provided by the environment. ERPsim is one such example of a simulation software that can offer an enactive learning environment (Léger et al., 2014). In addition to being used in higher education, ERPsim has also been used in corporate EUT contexts (Deranek, McLeod & Schmidt, 2017).

Learning Outcome	Focus	Example(s) of Outcome(s)
Skill	Focuses on the user’s ability to use the target system	Task performance
Cognitive	Focuses on conceptual knowledge	Comprehension, Knowledge
Affective	Focuses on the emotional aspects	Satisfaction, Anxiety, End-user satisfaction
Meta-Cognitive	Focuses on the user’s perception about their abilities or learning	Self-efficacy, Satisfaction with training program

Table 1. Learning Outcomes as classified by Gupta et al. (2010)

Nudges can be defined as “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid.” (Thaler and Sunstein, 2009). Nudges have been widely studied in behavioural economics and is gaining popularity as a research topic in other fields, notably in the health and environmental sectors. However, research in organizational settings is still lacking (Hummel & Maedche, 2019). The work presented in this thesis therefore answers the calls for research on nudging in other fields by Caraban et al. (2019) and Hummel and Maedche (2019). As more and more decisions are being made on screens, especially in businesses integrating ES, digital nudging has become an increasingly popular topic in information systems (IS) research. Digital nudging is defined as when an IS is involved in the delivery of the nudge (Weinmann et al., 2016). Digital nudging has advantages over traditional, offline nudging; they are easier, faster and cheaper to implement (Mirsch, Lehrer & Jung, 2017). Thus, digital nudging has interesting managerial implications as a cost-effective method of steering behaviour towards a desirable outcome.

Following the discussion from the introduction, nudges can be either reflective or reflexive. In a EUT context, reflective processes are important to learning. For example, a study showed that managers who made decisions based on their “gut feeling” had a harder time justifying their decisions (Elbanna et al., 2013). Therefore, we focus on nudges that are reflective. Various types of nudges can be considered as reflective. Based on a literature review presented in the second chapter of this thesis, we choose to focus on social and warning nudges. Social nudges use our innate desire to conform; by making others' actions more salient, individuals' actions can be influenced (Kretzer & Maedche, 2018). Warning nudges remind individuals of their consequences, thereby increasing the perceived risk of bad decisions, or they can direct them towards a piece of important information (Jung & Mellers, 2016; Caraban et al., 2019).

This thesis focuses on the design of nudges in an enactive, problem-solving context with the goal of supporting business simulations in developing EUT learning outcomes. The high cognitive load resulting from these games may be detrimental to learning, and this research project investigates the viability of nudges in counteracting this negative aspect of serious games that are used in EUT contexts.

The first article is a systematic literature review and its first goal is to deepen our understanding of training outcomes and how nudges can be designed to improve learning effectiveness. A second goal is to paint a landscape of the status of research on nudging in organizational and educational contexts and to propose research avenues.

Based on the literature and the research avenues proposed in the first article, the second tests, in an empirical study, two types of nudges, a social and a warning nudge. We aim to investigate their effectiveness in supporting training outcomes. In addition to measuring training outcomes, we also aim to understand how the learner's individual characteristics affect the effectiveness of nudging.

While research on nudges is abundant, nudging in this context has yet to be researched. This thesis is therefore motivated by the following research questions:

RQ1. Can training outcomes be positively influenced by digital nudging in an enactive EUT context?

RQ2. What type of digital nudge is more effective at supporting training outcomes in an enactive EUT context?

RQ3. Are the effects of digital nudging homogeneous across learners?

1.3 Theoretical and Practical Research Contributions

Theoretically, our research aims to contribute to the large body of existing nudging literature by exploring its effects in a field that has yet to be researched. We also aim to deepen the understanding behind the psychological mechanisms behind nudging in an end-user training context by incorporating the individual's characteristics, such as self-efficacy and prior experience in an experimental study.

From a practical standpoint, this thesis contributes to the understanding of the design of nudges with the goal of positively influencing end-user training outcomes. The results of the experimental study will allow us to offer recommendations on best practices when designing nudges in an enactive training context to improve learning effectiveness. The low cost and ease implementation of nudges within a digital setting has interesting implications for educators and trainers using serious games for e-learning. This thesis could help inform the design of training curriculums involving serious games as it pertains to EUT outcomes, as it can be a source of information for educators on potential biases that can occur during serious games and help them move towards strategies to mitigate these biases.

We also contribute from a methodological perspective by demonstrating that conducting a safe, remote experiment based on ERPsim is easily doable in extenuating circumstances, as the experiment was run during the COVID-19 pandemic.

1.4 Structure of Thesis

This thesis is structured into two articles. The first article is a systematic literature review and bridges the concepts of nudging and end-user training. Existing works on nudging are explored, and studies demonstrating the effectiveness of nudging are discussed. Research gaps on nudging studies within end-user training contexts are established. The goal of this literature is to motivate further research on this topic. The systematic literature review was submitted to the AMCIS 2021 proceedings in March 2021. The second article reports the results from the experimental study in a form of a scientific article and is being prepared for submission to the *Journal of Computer Information Systems* (JCIS). This article was written after the data collection and investigates the effectiveness of the designed nudges, as well as how individual characteristics affect the effectiveness of nudging on learners. To conclude, the main findings are reported and discussed, followed by the limitations of the study.

1.5 Article 1: Engaging reflection: A Systematic Review of Nudging in IS Training

1.5.1 Article 1

The first article is a literature review and presents the ongoing research on nudging and identifies research gaps within the literature. The primary goal of the literature review is to investigate the effectiveness of nudging and to understand the mechanisms behind its effectiveness in order to motivate research in other fields. The second goal is to contribute towards a theory-based experimental design. This article contributes to the literature by bridging the concept of nudging into an organizational learning context, and by proposing initial research avenues on this topic. A summary of the review is provided below.

1.5.2 Summary of Article 1

The article takes the form of a systematic literature review and starts by setting the context and the research questions, which is whether nudges have potential in improving learning outcomes in a training context, which type of nudge has stronger effects, and whether individual characteristics affect the effectiveness of nudging. Then, the theoretical foundations behind nudging and learning are laid out. A systematic review, based on several criteria, was then conducted. A total of 9 relevant studies were included. The literature suggests that nudges aimed at engaging reflective thinking are better suited when the goal is to enhance learning effectiveness. The result from this review process shows a significant research gap in this field, and that certain types of nudges have more potential than others in influencing learning outcomes. The review concludes by discussing its limitations and future research opportunities.

1.6 Article 2: The Effectiveness of Digital Nudging in End-User Training: Evidence from an Experimental Study

1.6.1 Article 2

The second article in the thesis is an empirical study and is currently in preparation for submission to the *Journal of Computer of Information Systems* (JCIS). The experimental design was based on the literature review from the first article, and the data collection was completed by the student of this thesis and a co-researcher in July 2020. A preliminary version of the article is presented in this thesis, as it has yet to be peer-reviewed by the journal. The results of the experimental study are reported and discussed. This article contributes to the literature by answering calls for empirical research of nudging, as well as investigating the external validity of nudging in other contexts. A summary of the second article is provided below.

1.6.2 Summary of Article 2

The article starts by laying out the context and the research questions. The background literature is presented, and hypotheses are developed. The objective of the experiment is to test 2 different types of nudges, a social and a warning nudge. The experimental platform, ERPsim (Léger et al., 2011) and design is then explained. In a between subjects experiment, we provided the participants with the same dashboard across all groups, designed with Tableau (Tableau, Seattle, United States). The experiment was done remotely, using Lookback.io (Lookback inc., San Francisco, United States), a user testing software. As this study was a between-subjects design, participants were exposed to either a no-nudge condition, the social nudge or the warning nudge.

The results of the experimental study, done with 64 participants over the month of July 2020 are reported and evaluated based on the third step of the nudge design process. Our findings indicate that the designed nudges were not successful in significantly improving learning outcomes. However, several moderating effects were found between the outcomes and self-efficacy and experience, suggesting that individual differences do affect the effectiveness of nudges. Specifically, the warning nudge had an adverse effect on decision confidence for lesser experienced individuals, but there was a reversal effect for those with higher experience, when compared with a control group. For those with a lower level of self-efficacy, the social nudge had a stronger effect on decision performance on those who had a higher level of self-efficacy, when compared with a control group and the social nudge group. These results indicate that warnings may not be the best nudge when dealing with novices, or low self-efficacious individuals.

The results are discussed in relation to other works, and further reinforces the fact that the effectiveness of nudges is largely dependent on context, rather than nudge type. Additionally, nudge designers must take into account the nudgee's individual characteristics, such as prior experience and level of self-efficacy. The article concludes by reiterating the hypotheses and results, the limitations of our study and future research opportunities based on the findings.

1.7 Personal Contributions

Step	**Contribution**
Research Question	Development of a research question - 90% ● Research question partially formed at the start of the project ● The research team contributed to the definition of the final research question and the approach to take
Literature Review	Review literature to identify research gaps in nudging in learning contexts and the identification of relevant constructs - 100%
Experimental Stimuli Development	Creation of the dashboards for the experiment - 95% ● Dashboards reviewed by members of the team Creation of the training material given to the participants for the experiment - 100% Modification of the stimuli after the pre-tests - 100%
Experimental Design	Creation of consent forms and recruitment messages - 100% Submission of the forms to the REB (Research Ethics Board) - 90% ● Subsequent modifications to the ethics approval was assisted by members of operations team Creation of the experimental protocol - 90%

	● Creation of the questionnaire assisted by another graduate student Creation of the training material given to participants for the experiment - 100%
Participant Recruitment	Creating the recruitment message template - 100% Recruitment and scheduling of participants for the study - 60% ● Assisted by another graduate student, who recruited a part of the participants for the study Participant compensation management - 60% ● Assisted by another graduate student, who managed a part of the participants for the study
Pre-tests and Data Collection	Pre-tests - 100% Data Collection - 60% ● Assisted by another graduate student, who recruited and moderated sessions for the participants he recruited
Data Analysis	Initial extraction and formatting of the data for statistical tests - 75% ● Initial data extraction and formatting assisted by another graduate student Subsequent formatting of the data for further statistical tests - 100% Statistical analysis - 90% ● Assisted by the statistician at the Tech3Lab
Drafting	Drafting of the two articles presented in this thesis - 100% ● The co-authors involved in the articles offered feedback

Table 2. Personal Contributions in the Drafting of the Articles

Chapter 2

Article 1 - Engaging Reflection: A Systematic Review of Nudging Interventions in IS training

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2.1 Abstract

Nudging has been extensively studied in behavioural economics as a tool to steer behaviour. However, it remains an under-researched topic within organizational contexts. As businesses move towards digital transformation and increasingly rely on enterprise systems, it is imperative to have well-trained users who can adequately leverage these systems. This digital landscape presents interesting opportunities for using digital nudges as a means to aid employee performance and learning. In this paper, we present a qualitative systematic review of nudging studies in information systems, with the goal of determining whether digital nudging can be a viable tool to influence learning outcomes and employee performance in an organizational context. We found 9 relevant empirical studies in the fields of business, health, education and social media. Our findings indicate that some nudges work better than others, notably social nudges, but that additional research is required for more conclusive results, and suggest future avenues for research.

Keywords
Nudge, Choice Architecture, Training, Qualitative Systematic Review, Enterprise Systems

2.2 Introduction

Today, businesses are required more than ever to have a solid understanding of Enterprise Systems (ES) and how to efficiently use these systems in order to remain competitive. However, ES initiation projects are often met with failures; 20% to 25% of ERP implementation initiatives end up in failure, and another 55% to 60% end with unsatisfactory or underwhelming results (Torii, 2020).

One of the biggest success factors in ES initiatives are its end-users; lack of satisfaction, or a system that is too complex or frustrating to use, decreases the likelihood of user acceptance and successful implementation (Gargeya & Brady, 2005; Saxena et al., 2016). ES are extremely complex; coupled with limited amounts of time to absorb knowledge before use, the high cognitive load and stress induced by the use of ES are some of the reasons for adoption failure (Rajan & Baral, 2015). Therefore, companies invest a significant portion into end-user training (EUT), as the inadequate use of ES is a hindrance to productivity or performance gains (Dezdar & Ainin, 2011; Scott & Walczak, 2009). In 2005, large companies in the U.S. spent $109.25 billion on EUT (Gupta et al., 2010). Studies have shown that EUT can significantly contribute to employee performance and acceptance (Gupta et al., 2010; Khan, 2012; Esteves, 2014). Unfortunately, these investments are often wasted; a survey across 50 organizations discovered that 70% of employees are not confident they have the required skills to perform their tasks adequately and only 12% of employees reported applying newly learned skills in their jobs (Glaveski, 2019).

In order to improve learning outcomes, educators in every context often employ the use of scaffolds, which refers to the assistance an educator provides a learner to help them achieve a task that would be otherwise unattainable (Vygotsky, 1980; Léger et al., 2011). Recently, a concept known as “nudging” has garnered interest. Nudges are small scale interventions that influence behaviour in a predictable way, without restricting freedom of choice (Thaler and Sunstein, 2009). Many aspects of scaffolding and nudging overlap. By using some elements of scaffolding and adapting them into a version of a nudge, there are interesting implications in terms of the research and development of nudges that can positively impact EUT outcomes.

The objective of this research is to deepen the understanding of how to design simple nudges with positive impacts on EUT and performance outcomes and to explore the effectiveness of nudges in a digital setting. Specifically, Our research question is: Do digital nudges have potential in improving learning and consequently, job performance in an EUT context? This study is important because few empirical studies have been conducted exploring the viability of nudges in an organizational context, specifically aimed at employees in training. We answer calls for intensifying research on digital nudging by Hummel and Maedche (2019) and Caraban et al., (2019), who have previously conducted systematic literature reviews on the subject.

The literature review is structured as follows: first, we develop the theoretical foundations behind nudging and EUT, followed by a qualitative systematic review of nudging studies related to an EUT context. Finally, future research opportunities are discussed.

2.3 Background Literature

2.3.1 Nudge Theory

Nudge theory is a concept popularized by Richard Thaler and Cass Sunstein in their book "Nudge: Improving decisions about health, wealth and happiness" (2009). They defined their concept as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid.". Popular examples of nudges include asking people if they would like to become organ donors when renewing their driver's license, or putting stickers of flies into the men's room urinals to improve aim and reduce spillage (Thaler and Sunstein., 2009). Nudging has been extensively studied in behavioural economics and in empirical experiments in the fields of policy and health (Sunstein, 2016; Marchiori, Adriaanse & De Ridder, 2017). In short, nudges aim to drive people towards better decisions, without restricting their freedom of choice.

The concept of nudging is based on the dual process theory, which was popularized in Daniel Kahneman's book "Thinking Fast and Slow" (2011). The dual process theory explains how thought processes are divided into two systems: a fast, automatic and unconscious system, and a slow, deliberate and conscious system. These systems are referred to as System 1 and System 2 respectively (Kahneman, 2011). System 1 is the primary driver for most of our daily tasks. Automated thinking is generated without much cognitive effort and relies on pattern recognition based on past experiences (Tay, Ryan & Ryan, 2016). System 2, on the other hand, comes through conscious effort. Performing complex arithmetic operations or recalling a phone number are examples of System 2 operations (Kahneman, 2011). However, System 2 is only effective given that the decision-maker has sufficient cognitive resources (Rottenstreich, Sood & Brenner, 2007).

Nudges work by using our limited cognitive resources; humans are cognitive misers and often use heuristics, mental shortcuts that simplify the task at hand (Tversky & Kahneman, 1974; Samuelson & Zeckhauser, 1988; Gigerenzer et al., 2011; Haselton, Nettle & Murray, 2015). For example, since people lack preferences, clear information and motivations, they are more likely to take the path of least resistance in terms of cognitive effort and can therefore be influenced by default choices, framing of the information and starting points (Marchiori et al., 2017). Alternatively, nudges can also trigger reflective processes, by using warnings or reminders (Jung and Mellers, 2016). In an EUT context, where deliberation and problem-solving are crucial to the process of learning, nudges can offer an interesting method of further recruiting System 2 within learners to positively impact EUT outcomes.

Digital nudging is gaining relevance as more decisions are made on screens and follows the same definition of Thaler and Sunstein's nudge, but is specifically characterized by the inclusion of an IS in the nudge (Weinmann et al., 2016). ES increase the amount of information that is accessible; more decision support is required to prevent information overload (Lembcke et al., 2019). Digital nudging has interesting managerial implications, since it has advantages over traditional, offline nudging. Notably, they are usually cheaper, faster, and easier to implement than traditional nudges. They also offer more flexibility; the online nature of digital nudges allows for the collection of user behaviour data, which in turn can be used to design and deliver personalized, targeted nudges (Mirsch et al., 2017).

2.3.2 End-User Training

End-user training has an enormous organizational impact and is the most common way of enhancing employee productivity, constituting 38.4% of all types of corporate training. The goal of EUT is to produce a motivated user who has the necessary skills to perform a job-related task (Gupta et al., 2010). Igbaria, Guimaraes & Davis (1995) found that proper training has a significant positive effect on technology adoption, as they increase a user's abilities, and consequently their confidence in their use of the technology.

Wood, Bruner and Ross (1976) introduced the concept of scaffolding, which refers to the assistance provided by an educator or a peer to support the learner. Providing the learner appropriate assistance can give them enough of a boost to achieve a certain task that they otherwise would not have been able to. Scaffolding should also ensure that they learn from the experience (Vygotsky, 1980; Léger et al., 2011). Some examples of scaffolding techniques include maintaining the learner's interest and participation in the task, simplifying the task, emphasizing certain aspects that will help the learner complete a task, etc (Silver, 2011). Feedback is an indispensable tool for learning, but the value of the feedback is mostly dependent on the learner's understanding of the context and material. Barring this, learners would have difficulty in understanding and using the feedback (Weaver, 2006). Therefore, whenever an educator is providing assistance, it is important to accurately assess the learner's current knowledge and experience, as every learner has a different level of knowledge and skill (Silver, 2011). Many aspects of scaffolding overlap with nudging; Sunstein (2014) describes simplification nudges that present information in a digestible manner, precommitment strategies that increase the likelihood of a behavior by asking people to commit to an action in the future, etc. These types of techniques are certainly not novel for educators. Existing scaffolding techniques can therefore serve as a good starting point for nudge designers.

2.4 Methodology

2.4.1 Systematic Literature Review

We conducted a qualitative systematic literature review, a method that is suitable for our aims of synthesizing the published evidence narratively (Schryen et al, 2020). We executed the search on Web of Science, produced by Clarivate Analytics (Philadelphia, United States). Web of Science is a collection of databases that includes articles, conference proceedings and books from various fields in science. We looked for articles in English, published in a peer-reviewed journal after 2007, as nudging studies only started appearing after 2008 due to Thaler and Sunstein's (2009) initial work on nudging.

The first search term used was [*nudg** OR "*choice architecture*"]. Following this, 2 additional AND statements were combined with the first pair of keywords. The first AND statement consisted of the keywords [*"digital" OR "online", "smartphone" OR "computer" OR "information system*" OR "information technolog*"*]. The final part of the query included the keywords ["*teach**" OR "*learn**" OR *"train*"* OR "*educat**"OR or "*perf**"]. Within the query, the asterisks correspond to a wildcard, which allowed us to search for all permutations of a certain word (e.g. nudg* can return nudging, nudge, nudges, etc). Figure 1 represents the screening process used to eliminate non-relevant studies.

Our initial search returned 91 hits. These results were exported to an Excel spreadsheet for further screening. The initial screening consisted of keyword searches for "nudg*" and "choice architecture" in the title, paper keywords and abstract. 36 records were eliminated. The second screening was based on three inclusion criteria. First, the study had to be empirical in nature. We therefore screened out conceptual papers or reviews. Second, the study must mention the concept of digital nudging as defined by Thaler and Sunstein (2009) or Weinmann et al. (2016). Several studies only mentioned nudges in passing, used it as a verb and not as a concept or were not digital in nature. Third, the study must have an educational or organizational context, as we are interested in the effects of nudging on learning outcomes and performance. The second screening eliminated 48 records. Finally, 2 records were added through snowballing, for a total of 9 studies to be included in our analysis.

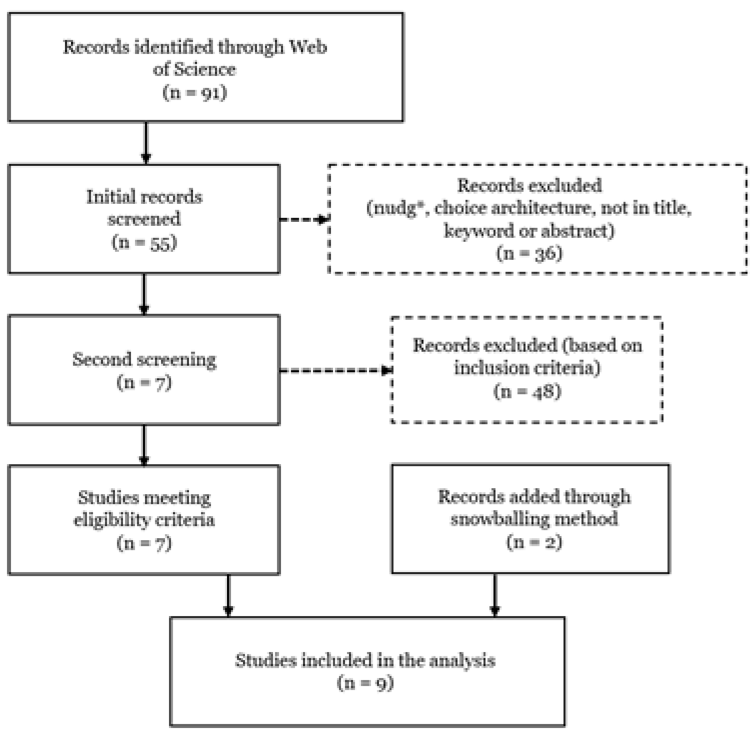

Figure 1. Study Screening Process

2.4.2 Coding

After obtaining a final list of studies to be included, we extracted information from the studies and systematically stored them in a spreadsheet and analyzed them accordingly. First, information such as the author(s), title, name of the journal and publication year were extracted. Then, we identified the context of the study. Finally, we searched for the nudge(s) used in the experiment and its different characteristics, such as the goal of the nudge, whether the nudge targets Systems 1 or 2, whether the nudge is homogeneous or heterogeneous across participants, its delivery format and its effectiveness. For characteristics having to be inferred from the text, which were limited to the target of the nudge (System 1 or 2) and the homogeneity of the intervention, the second author coded this data as well to test for inter-rater reliability. Cohen's $\boldsymbol{\kappa}$ was run using IBM SPSS (IBM, Chicago, United States) for both characteristics; a strong agreement was observed for the target coding ($\boldsymbol{\kappa}$ = .683, $p < .01$), and a perfect agreement for the homogeneity coding ($\boldsymbol{\kappa}$ = 1,0, $p < .0001$).

2.5 Results

2.5.1 Publication Year and Context

Figure 3 presents the publication year and context of the nudging studies. The earliest publication year of the included studies was 2015, and the most recent was 2020. Even though studies related to nudging started appearing after Thaler and Sunstein's (2009) work in 2008, studies with potential relevance to our context are quite recent. As for categories, a majority of the included studies were in educational (n = 3) and business (n = 3) settings, followed by healthcare (n = 2) and social media (n = 1).

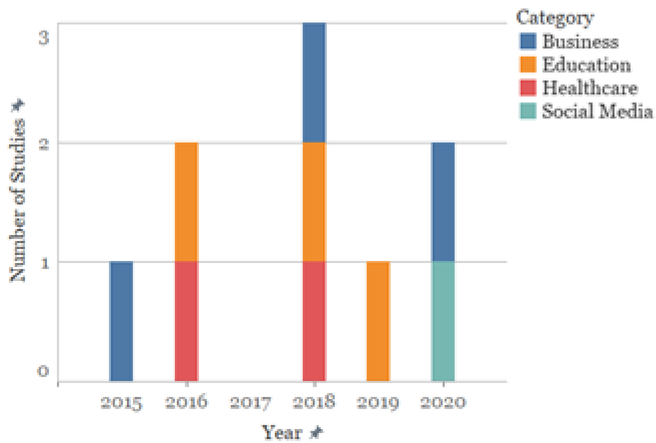

Figure 2. Publication Year and Categories

2.5.2 Overall Analysis of the Nudges

To analyze the different nudges used in the study, we broke down the interventions into several dimensions. Table 1 presents the different nudges that were tested in the included studies. We used Sunstein's (2014) and Münscher et al.'s (2016) existing framework for classifying choice architecture tools, as most authors used these frameworks to select their nudges. The most used nudge was social norms (5 studies), followed by framing, reminders, default and priming (2 studies each), which were equally used. Incentive, salience and informational nudges were the least used (1 study each). 3 studies out of 9 tested a combination of nudges.

The nudges were evaluated based on their objectives. Nudges were considered effective if the authors reported positive, statistically significant results. 9 out of the 14 nudges described were reported as effective. A meta-review by Hummel and Maedche (2019), comprising an analysis of 317 effect sizes, found that 62% of nudges were successful at influencing behaviour. While our review contains a small number of studies, we report a success rate of 64%, which corroborates these results. Caraban et al. (2019) also found similar results, with a reported success rate of 66%. In terms of successful nudges, social nudges came out on top with a 100% success rate (5 out of 5) whenever it was used. Priming and reminders also enjoyed a 100% success rate (2 out of 2). Defaults and framing had mixed results (1 out of 2), and none of the precommitment strategies or the informational nudge were successful (0 out of 2, 0 out of 1, respectively).

#	First Author (Year)	Context	Nudge	Targeted?	Type of Nudge	Effective?
1	Pennycook, G. (2020)	Social Media	Priming	No	Non-transparent, Type 2	Yes
2	Bammert, S. (2020)	Business	Incentive	No	Non-transparent, Type 2	Yes
3	Bammert, S. (2020)	Business	Salience	No	Non-transparent, Type 2	Yes
4	Bammert, S. (2020)	Business	Precommitment	No	Transparent, Type 2	No
5	Bammert, S. (2020)	Business	Default	No	Non-transparent, Type 1	No
6	Bammert, S. (2020)	Business	Information	No	Transparent, Type 2	No
7	Lawrence, J. (2019)	Education	Reminder and Social	Yes	Transparent, Type 2	Yes
8	Patel, MS. (2018)	Healthcare	Framing	No	Non-transparent, Type 2	No
9	Patel, MS. (2018)	Healthcare	Social	No	Non-transparent, Type 1	Yes
10	Baker, R. (2016)	Education	Precommitment	No	Transparent, Type 2	No
11	Malhotra, S. (2016)	Healthcare	Default	No	Non-transparent, Type 1	Yes
12	Martinez, S. (2015)	Business	Priming and Framing	No	Non-transparent, Type 1	Yes
13	Kretzer, M. (2018)	Business	Social	No	Non-transparent, Type 1	Yes
14	O'Connell, S.D. (2018)	Education	Reminder and Social	No	Transparent, Type 2	Yes

Note: Some authors appear more than once because they tested more than one type of nudge (different treatments) within the same study
Note: Some interventions combine types of nudges instead of considering them as separate treatments, as is the case for Lawrence (2019), Martinez (2015) and O'Connell (2018).
Note: An intervention was successful if the study reported positive effects at $p > 0.05$

Table 3. Nudges Included in the Analysis

2.5.2 Social Nudges

The most commonly used and successful type of nudging was social norms. In all 5 studies, the social nudge was effective at influencing behaviour by using peer comparison. Kretzer and Maedche (2018) found that social nudges with high social cohesion (how closely an individual can relate with another), high institutional isomorphism related to position (how similar an individual's position is to the comparison point; for example, there is high institutional isomorphism if the two individuals occupy the same position) and high hierarchical power (upper levels of the hierarchy have more power than the lower levels) were more effective than nudges that were low on these dimensions. Patel et al. (2018) did a field experiment and used the clinician's peers as a point of comparison; we believe the successful change in behaviour to be partly attributable to the high social cohesion and institutional isomorphism used in the nudge. This is also the case for O'Connell and Lang (2018), and Lawrence et al. (2019), who used the student's peers as the point of comparison.

Reminders were also quite successful. In both studies (O'Connell & Lang, 2018; Lawrence et al., 2019), the students were reminded with short messages to encourage them to invest time in their course-related material. However, the reminder nudges were both combined with a social nudge. Therefore, we have no data on whether purely informational reminders would be successful in other contexts.

2.5.3 Incentive, Salience, Framing and Priming Nudges

The incentive and salience nudges were also successful, but they were only tested in one study (Bammert et al, 2020). These nudges used the regret aversion bias by informing the participants, through a notification, of the financial consequences of a job poorly done. Martinez and Pérez (2015) were also successful in significantly speeding up survey completion times by adding a digital clock on the interface, which served as their framing and priming nudge by implementing a 15 minute countdown. They speculated that by using a 15 minute frame, participants would want to finish their task faster due to the regret aversion bias. We also believe that the priming nudge by Pennycook et al. (2020) worked on the same principle; by instilling doubt, people make more careful decisions because of the regret aversion bias. The other study that tested a framing nudge was unsuccessful at changing behaviour; Patel et al. (2018) aimed to increase clinician's prescription rates by prompting an immediate decision (active choice). With different contexts and biases underlying each study, combined with the small sample size, we cannot make meaningful interpretations as to the effectiveness of these nudges.

2.5.4 Precommitment, Default and Informational Nudges

Both precommitment nudges failed in either studies that tested them. Bammert et al. (2020) did not offer any insights as to the results obtained, but Baker, Evans and Dee (2016) suggest that the participants did not think pre committing to a certain course of action would be useful, or that they believed they did not require or appreciate the help.

Bammert et al. (2020) also tested default and informational nudges, both of which were not successful. The author did not discuss as to why the informational nudge failed. In the same study, the default nudge backfired and actually lowered task performance. Malhotra et al. (2016) also tested a default nudge, and the study reported a resounding success. We suspect the reason for this difference is simply the goal of the task; in the former study, sticking with status quo represented a bad outcome, whereas in the latter it was a positive outcome. This implies setting defaults to the current state will backfire when the goal is to leave the status quo.

2.5.5 Targeted nudging

In terms of personalization, all the nudges included in our study were homogeneous across participants, save one; that is, all participants received the same version of the nudge. Only Lawrence et al. (2018) tested personalized nudges, using analytics to collect information, which allowed them to tailor nudges to each participant. They specifically targeted low or non-engaged participants in an educational context, and delivered nudges based on various templates depending on criteria outlined by the research team.

2.5.6 Engaging reflection with nudging

We analyzed the type of nudge according to Hansen & Jespersen's (2013) categorization framework and is based on transparency and whether it engages reflective thinking or not. Transparent Type 2 nudges engage reflective thinking and allows the nudgees to recognize the means through which their behaviour was influenced. Transparent Type 1 nudges do not engage reflective thinking, but still allow the nudgees to recognize the means through which their behaviour was influenced. Non-transparent Type 2 nudges engage reflective thinking, but the reasons behind the change in behaviour are not so easily recognized. Framing a situation in terms of risks, or providing social norms can provoke affective processes, which can then trigger reflective thinking. Finally, Non-transparent Type 1 nudges influence behaviour subconsciously in a way that is not easily recognizable. The types of nudges were approximately evenly distributed between non-transparent (n = 5) and transparent type 2 (n = 5), and non-transparent type 1 (n = 4). Therefore, it seems like nudges aiming to improve learning outcomes or performance most commonly aim to engage reflective thinking, but were evenly split between transparent and non-transparent nudges.

2.6 Discussion

Through a systematic review of the literature, we found a total of 9 relevant studies that could potentially be relevant to an organizational, EUT context. Our analysis found that research within this particular field is still few and far between.

We found that social nudges have a higher potential to successfully change behaviour compared to other nudges; social norms seem to have a very strong influence on behaviour. Other nudges yield mixed results or have weak external validity due to the low sample size of this review. The regret aversion bias was also observed often, however this was implicitly discussed in most of the studies. This implies that fear can be a potentially strong mechanism to nudge behaviour (Caraban et al., 2019).

Only one study out of 9 tested personalized nudging. This is presumably due to the higher cost and effort that is required in collecting behavioural data to create tailored interventions. The format of the nudge will also be dependent on the situation and the goal of the intervention. In educational contexts, we highlighted the importance of considering the learner's level of knowledge and competencies (Silver, 2011). Scaffolding is most effective when matched with the learner's needs (Wood et al., 1976). Targeted inventions can also potentially be more effective than non-targeted interventions (Damgaard & Nielsen, 2018).

From an ethical standpoint, the main criticism against nudging is its potential to be manipulative. Nudges aimed at System 1 often drive behaviour unconsciously and can be, more often than not, go unnoticed by the nudgee (Thaler and Sunstein., 2009). One can argue that nudges that target unconscious processes can be perceived as manipulative; if the nudgee is not aware they are being influenced, they cannot make an informed choice (Lembcke et al., 2019; Junghans et al., 2015). From a practical standpoint, nudges are also heavily criticized for its inability to change behaviours over a longer period of time. Once the intervention is removed, behaviour often reverts to the pre-intervention state (Hertwig and Grüne-Yanoff, 2017; Bond, 2009). Other nudges depend on the nudgee not knowing he or she is being nudged, as the response needs to be unconscious (John and Stoker, 2017). The result of these criticisms is the development of nudges that are more transparent and that are more effective in the long term, such as "nudge plus" (John and Stoker, 2017) and "boosts" (Hertwig and Grüne-Yanoff, 2017), which aim to educate and foster competencies instead of focusing on changing immediate, unconscious behaviour.

Our findings indicate that when it comes to influencing learning outcomes or performance, nudges that attempt to engage reflective thinking are more common. Most organizational tasks and learning require some conscious processing; influencing learning outcomes or job performance is very hard to do unconsciously. Nudges such as framing and social norms may trigger unconscious processes that may influence behaviour, but effort must still be expended to learn new concepts, or to perform a task well. There are a few exceptions to this; one such example is the use of default nudges, which can lead to better performance, without much thought or effort expended (Malhotra et al., 2016).

2.7 Conclusion

In this paper, we attempt to demonstrate a research gap in nudging studies done in an organizational context. Research regarding organizational job performance is scarce, and to our knowledge, we are the first to investigate nudging specifically within an end-user training context. Previous work indicates that some nudges can have potentially stronger effects than others, as is the case with social nudges. However, more research is required in order to reach conclusive insights on the effectiveness of nudging within this context, due to the small amount of studies included in the review. This paper also demonstrates that digital nudging can be a viable tool for influencing behaviour as it relates to educational and performance outcomes, if used correctly. This work contributes to the literature by presenting an initial exploration of nudging in an organizational context to influence learning and performance and attempts to direct future research towards nudges that may have the highest chances of success.

2.7.1 Implications for Research

We call for further research with a wider variety of nudges, targeted or non-targeted, that are transparent and that aim to engage reflective processes within an organizational context. We also call for further research using enactive training platforms, such as gamified simulations, as this coincides with the recent boom of simulations as training tools and allows researchers to investigate both learning outcomes and job performance at the same time. As such, we propose the following research avenues.

The first potential stream of research involves further testing other types of nudges that have been less studied in literature related to organizational, end-user training and performance contexts on different platforms. There are a wide variety of nudges that have yet to be tested for effectiveness within this field. The second potential stream of research we see involves testing personalized nudges, and comparing whether they are more effective than non-targeted nudges. There is also the question of effort versus added value, as personalized nudges will require more effort to implement. The third potential stream of research involves testing nudges that engage reflection, as they seem more suited to goals such as improving learning outcomes, and in some cases, employee performance. This is also in line with calls for research concerning "nudge plus" (John and Stoker, 2017), and "boosts" (Hertwig and Grüne-Yanoff, 2017).

2.7.2 Limitations

We identified several limitations with our review. First, the nomenclature for nudging is extremely varied, and accounting for all of them is a difficult task. It is a certainty that some empirical studies fitting within the criteria of nudging were done, but that did not refer specifically to nudging or choice architecture. It is possible that our search criteria were too strict, and relevant studies may have been glossed over, resulting in the very small number of studies included in our analysis. Different authors have varying classification frameworks for nudges (Hansen & Jespersen, 2013; Munscher et al., 2017; Caraban et al., 2019), which shows that the literature is quite varied. Second, previous meta-reviews show that nudges are not always successful (Hummel & Maedche, 2019; Caraban et al., 2019). However, there may be a publication bias where research with unsuccessful nudges were not published, therefore making the real success rates of nudges lower than what is reported in the literature.

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Chapter 3

Article 2 - The Effectiveness of Digital Nudging in End-User Training: Evidence from an Experimental Study

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3.1 Abstract

"Digital nudges" are unintrusive, small interventions that are delivered via a digital medium, aiming to steer behaviour towards a desirable direction. This study investigates the effectiveness of 2 types of digital nudges, a social and warning nudge, as tools to assist end-user training (EUT). A between-subjects experiment with 64 participants was conducted with 2 treatment groups. The results show that the nudges failed to significantly influence performance and self-confidence in players of a business simulation game. However, task self-efficacy (TSE) and experience was found to be a moderator between the type nudging and training outcomes. The warning nudge had adverse effects for performance and confidence on novices and those with low TSE, while it had a positive effect on experts and individuals with high TSE. The social nudge however, had positive effects on decision performance for those with lower TSE, but the opposite was observed for those with higher TSE. Our results contribute to the theoretical understanding of how nudges work, and for nudge designers towards more effective nudges by suggesting that personalized nudges may be more effective in an EUT context.

Keywords: Digital Nudging – Enterprise Systems - ERPsim - Learning - End-User Training

3.2 Introduction

End-user training (EUT) has an enormous organizational impact and is the most common way of enhancing employee productivity in regards to Enterprise Systems (ES) usage, constituting 38.4% of all types of corporate training. The goal of EUT is to produce a motivated user who has the necessary skills to perform a job-related task and consequently increase the likelihood of user acceptance of an IT (Gupta et al., 2010; Rajan & Baral, 2015). Unfortunately, investments in EUT are often wasted as not all employees apply their learned skills to their work (Esteves, 2014; Jasperson, Carter & Zmud, 2005).

Studies have demonstrated that active teaching strategies can lead to better learner outcomes, usually by increasing engagement (Miller, 2004; Michel, Cater & Varela, 2009). To this end, simulation-based methods have seen a surge in popularity as a method for end-user training (EUT) (Zhongghen, 2019). Simulations provide an enactive learning environment that allows users to apply management theory and develop tool-based skills (Léger, Davis et al., 2014). Simulations have the added benefit of creating a safe environment in which learners can experiment and learn from the consequences of their decisions (Léger et al., 2012). Simulations also have their downsides; while they increase learner engagement, they also generate more cognitive load, which is potentially detrimental to learning effectiveness (Zhonggen, 2019).

Many strategies can be used to support learning. Educators often employ scaffolds to provide learners with just enough assistance to achieve a task that would be otherwise unattainable without help (Vygotksy, 1980; Léger et al., 2011). Scaffolds can take many forms, some attempt to simplify the task at hand or emphasize a piece of information while others try to maintain the learner's interest and participation (Wood et al., 1976).

One strategy that has yet to be explored in a EUT context is nudging. Nudging is a simple, non-intrusive push that encourages a particular behaviour (Thaler & Sunstein, 2009). Examples include providing additional information, using social comparison between peers (Damgaard & Nielsen, 2018). Like scaffolding, nudging can take a variety of types. Some are more subtle, such as the automatic enrollment in a pension plan. Others are more explicit, like graphic warnings on cigarette packages (Sunstein, 2014). Both scaffolding and nudging aim to give individuals decision assistance. Which type of nudge to choose ultimately depends on the goal and context. Digital nudging in particular is gaining relevance as more decisions are made on screens. Digital nudging is defined when an information system (IS) is involved in the nudge (Weinmann et al., 2016). Digital nudging has interesting managerial implications, since it has advantages over traditional, offline nudging. Notably, they are easier, faster and cheaper to implement (Mirsch et al., 2017).

The primary purpose of this research is to investigate the potential of digital nudges as an inexpensive and easy way to impact EUT in an enactive context to enhance learning outcomes.

Nudges have been extensively studied in the health, environment and finance sectors, but studies in education and business remain scarce (Szaszi et al., 2018; Caraban et al., 2019). To our knowledge, we are the first to explicitly study digital nudging in an EUT context. We also answer the calls for intensifying research on digital nudging by Weinmann et al. (2016). This study is motivated by the following research questions:

RQ1. Can training outcomes be positively influenced by digital nudging in an enactive EUT context?

RQ2. What type of digital nudge is more effective at supporting training outcomes in an enactive EUT context?

RQ3. Are the effects of digital nudging homogeneous across learners?

In order to address our research question, we designed two different types of digital nudges aimed at helping decision-makers in an enactive learning context. In order to assess the effectiveness of the nudges, we conducted a between subjects experiment with 64 participants.

This paper first presents background literature on EUT and nudging in order to develop our hypotheses. We then outline our methodology and report the results of the experiment. Finally, we discuss our findings and conclude by discussing the limitations or our study and future avenues for research.

3.3 Background Literature and Hypothesis Development

3.3.1 End-User Training and Simulations

Every training program must have goals; that is, the desired outcomes of the training process. These can vary according to the system that is being learned. Training outcomes can be either related to performance (types of errors, comprehension) or motivation (attitude towards the system) (Bostrom, Olfman & Sein, 1990). For the purposes of our research, we focus on 2 goals within an enactive EUT context.

The first training outcome we focus on are skill-based training goals. The primary objective of EUT is to develop the learner's competencies relating to the use of the target system (Gupta et al., 2010). Business simulations aim to improve the learner's decision-making skills in a safe environment, while interacting with a system that mirrors one they would use in a real-life scenario; this in turn, also offers opportunities to teach tool-based skills (Ampountolas, Shaw & James, 2019; Dick & Akbulut, 2020).

The second training outcome we focus on are affective goals, which focus on the learner's attitude (Gupta et al., 2010). Affective outcomes are equally important for user acceptance of an IS. Studies have shown that increased self-confidence can lead to higher intrinsic motivation and performance (Kloosterman, 1988; Bernard & Senjayawati, 2019; Kazimoglu, 2020). Highly motivated individuals will tend to invest more effort, resulting in better learning outcomes and performance (Brookhart, Walsh & Zientarski, 2006; Ampountolas et al., 2019). Research has shown that simulations are able to meaningfully impact affective outcomes, such as engagement, perceived self-competence, satisfaction, and perceived achievement of learning (Charland et al, 2016; Utesch et al., 2016; Paulet & Dick, 2019; Dick & Akbulut, 2020).

Empirical studies evaluating skill-based goals almost universally use task performance as a measurement, while motivation, satisfaction, anxiety and various attitudinal measures are common for evaluating affective goals (Gupta et al., 2010). Following these studies, we use in-game performance and confidence in decision-making as our skill-based and affective goals, respectively. The designed nudges should therefore attempt to aid the simulation in developing these competencies in users.

3.3.2 Nudge Theory

Nudge theory is a concept popularized by Richard Thaler and Cass Sunstein in their book "Nudge: Improving decisions about health, wealth and happiness" (2009). They defined their concept as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid.". Digital nudging involves the use of an IS and has recently garnered interest in the IS field as a tool to combat cognitive biases (Weinmann et al., 2016).

Nudging is based on the dual process theory, which theorizes that thought processes are divided into two systems: System 1, which is responsible for automatic and intuitive thinking, and System 2, which is more effortful and deliberate. System 1 is often associated with cognitive biases that lead to suboptimal strategic decision-making (Kahneman, 2011; Sunstein, 2016).

Nudges can offer decision assistance in a variety of ways. Nudges work because we humans are cognitive misers. Lack of preferences, clear information and motivation leaves us susceptible in taking the path of least resistance in terms of cognitive effort, and can therefore be influenced by default choices, how information is framed and starting points (Marchiori et al., 2017). Some target exclusively unconscious processes, while others can promote reflective thinking (Jung & Mellers, 2016).

This is where nudges differ from scaffolding, as they can drive behaviour unconsciously. For example, narrowing the sidelines of a street causes drivers to unconsciously slow down (Hansen & Jespersen, 2013). These types of reflexive nudges tend to be ineffective in the long run, as behaviour is usually reverted when the nudge is removed (Hertwig & Grüne-Yanoff, 2017). Therefore, nudges targeting purely System 1 will not result nor assist in the acquisition of competencies. As such, we concentrate on nudges that recruit System 2, as we believe they are better suited for an EUT context.

A variety of nudges can be construed as “System 2” nudges. The first type we investigate are based on social norms. By making the actions of others visible, people’s behaviour can be influenced due to our innate desire to conform. To be effective, social nudges should select appropriate comparisons that the nudgee can easily relate to (Sunstein, 2014; Caraban et al., 2019). Nudges using social norms can be conscious, as we deliberately choose to act like everyone else (Dolan et al., 2012). Studies have shown that social norms can be successful at increasing task performance (Colusso, Hsieh & Munson, 2016; Kretzer & Maedche, 2018; Patel et al., 2018). Based on these studies, we hypothesize that social nudges that guide users based on the actions of others can also be used in a business simulation context to improve performance.

H1: The social nudge will positively impact decision performance

The effects of social comparison are especially strong in situations of uncertainty, as we look to other’s conduct in order to validate the appropriate course of action (Festinger, 1954; Caraban et al, 2019). We therefore hypothesize that in an enactive problem-solving context, social nudges will act as a form of validation on the appropriate actions to take.

H2: The social nudge will positively impact decision confidence

The second type of nudges we focus on are warnings. These nudges remind individuals of the consequences of their actions (Caraban et al., 2019). They can also direct an individual's attention to an important piece of information or encourage vigilance (Jung & Mellers, 2016). Warnings have been shown to be more effective when accompanied with concrete steps to reduce the risk associated with the consequences (Sunstein, 2014). As with social norms, warnings have also been shown to have some effect on decision-making (Raschke & Steinbart, 2008; Esposito et al., 2017; Schneider & Graham, 2017). This leads us to hypothesize that warning nudges that remind decision-makers of the consequences of bad decisions will lead them to be more careful, thereby increasing their performance in a business simulation context.

H3: The warning nudge will positively impact decision performance

However, unlike social norms which seek to reinforce behaviours, warnings can generate feelings of skepticism or uncertainty via the loss aversion bias, where individuals will perceive an increase in risk and potential losses associated with bad decisions (Nekmat, 2020). This brings us to hypothesize that warnings will actually reduce decision confidence.

H4: The warning nudge will negatively impact decision confidence

In the context of our study, both the social and warning nudge are educative and should not explicitly tell the learners what to do, but rather to engage reflective processes (Thaler and Sunstein, 2009). However, in the context of our research, these types of nudges differ in the type of assistance they provide. Social nudges make the actions of others more visible, and is fairly easy to understand and apply, since learners can simply copy the behaviour of others. Warning nudges on the other hand, even accompanied with concrete steps to mitigate bad decisions, require the learner to first understand the consequences of their decisions, then apply the suggested steps to their decision-making process, which is not as simple as copying behaviour. In other words, within the context of our study, we consider the assistance that social nudges provide to be more directed and cognitively easier to apply than the one provided by the warning nudge. Therefore, we suggest that in the short term, the social nudge will have a stronger effect on in-game performance than the warning nudge.

H5: The social nudge will have a greater positive impact on decision performance when compared with the warning nudge

Since we previously suggested that warning nudges will reduce decision confidence, it stands to reason to believe that the social nudge will have a stronger effect on decision confidence than the warning nudge.

H6: The social nudge will have a greater positive impact on decision confidence when compared with the warning nudge

3.3.3 Impacts of Perceived Self-Efficacy and Experience on ES Use and Nudging

The Technology Acceptance Model (TAM) assumes that IS acceptance is determined by perceived usefulness (PU) and perceived ease of use (PEU) of the IS (Davis, 1989). In turn, many external variables can affect PU and PEU, such as anxiety, prior usage and experience, self-efficacy and confidence in technology (Marangunić & Granić, 2015). EUT can certainly impact these variables (Gupta et al., 2010). While our study isn't exhaustive, we chose to focus on self-efficacy and experience as moderating variables between nudging and the learning outcomes, as these are well studied.

Research has found that self-efficacy plays a large role in increased PU and PEU (Mun & Hwang, 2003; Park, 2009). Computer self-efficacy has been extensively studied in IS and is defined as one's belief about one's capabilities to perform computer related tasks (Compeau & Higgins, 2015). Individuals with higher self-efficacy are likely to invest and maintain more effort and achieve better learning and performance outcomes (Cherian & Jacob, 2013). Compared with the more general computer self-efficacy, research suggests that task-specific self-efficacy (TSE) has a stronger relationship with performance (Chen, 2017). Learners with low self-efficacy often need more directed assistance in order to boost their confidence and performance levels (Margolis & McCabe, 2005). Based on this, as the social nudge provides more direct assistance, we hypothesize that low self-efficacious learners will benefit more from this nudge over the warning nudge, and vice-versa.

H7: Task Self-Efficacy moderates the relationship between decision performance and social nudges, such that the lower the level of TSE, the more positive the effect of the social nudge

H8: Task Self-Efficacy moderates the relationship between decision performance and warning nudges, such that the higher the level of TSE, the more positive the effect of the warning nudge.

H9: Task Self-Efficacy moderates the relationship between decision confidence and social nudges, such that the lower the level of TSE, the more positive the effect of the social nudge.

H10: Task Self-Efficacy moderates the relationship between decision-confidence and warning nudges, such that the higher the level of TSE, the more positive the effect of the warning nudge.

Research has also found that having prior experience with a technology increases the chances of IS adoption (Kim, 2008). Experts often think differently than novices; experts often employ System 1 in order to make intuitive decisions, thereby saving a great deal of cognitive effort (Kraiger, Ford & Salas, 1993). Additionally, experts also differ from novices with regards to problem solving strategies; for example, they reflect on their strategies and monitor their progress, generally have a more positive attitude, etc (Léger et al., 2010; Léger, Riedl & Vom Brocke, 2014).

Interventions that encourage the expenditure of effort can improve decision quality, but only if the decision-maker has the requisite knowledge that can translate into better performance (Raschke & Steinbart, 2008). Based on this, we hypothesize that since novices have less prior experience about the decision at hand, the warning nudge may not be as effective as the social nudge in improving performance or decision confidence. We expect experts to have the requisite knowledge about ES acquired via prior experience, to better understand and apply the warning nudge than novices.

H10: Experience moderates the relationship between decision performance and social nudges, such that novices will benefit more from this nudge than will experts.

H11: Experience moderates the relationship between decision performance and warning nudges, such that experts will benefit more from this nudge than will novices.

H12: Experience moderates the relationship between decision confidence and social nudges, such that novices will benefit more from this nudge than will experts

H13: Experience moderates the relationship between decision confidence and warning nudges, such that experts will benefit more from this nudge than will novices.

3.4 Materials & Methods

3.4.1 Experimental Design

To test our hypotheses, we used a between-subjects experimental design, with decision performance and decision confidence as our dependent variables. The treatment was the type of nudge. This factor had 2 levels; a social nudge and a warning nudge.

3.4.2 Sample

A convenience sample of 67 participants was used for this study, but 3 were dropped due to low data quality and non-completion of the experiment. Among the 64 valid samples, 52% were female (n = 33) and the rest were male (n = 31). The participants were aged 20 – 39, with an average age of 26 (median = 26, SD = 3.96). A majority of the participants had obtained a Bachelor's degree (n = 35), followed by a Master's degree (n = 20) and Ph.D (n = 4). The remaining 5 had not completed a Bachelor's degree, but were enrolled in an undergraduate program at the time of the experiment. The study was approved by our institution's Research Ethics Board (certificate number 2021-3926).

3.4.3 Procedure

Data was collected remotely using Lookback (Lookback Inc, California, US), a platform which allows for real-time moderated testing. Participants were required to have access to a computer, a microphone, a webcam and an Internet connection faster than 5 mbps to participate in the study. All participants signed a consent form and were compensated with an Amazon gift card for their participation at the end of the session.

Participants were required to answer a pre-task questionnaire for demographics information and to measure their perceived task self-efficacy and level of experience. Then, they viewed a short video explaining how to play the game. Participants then played 2 rounds of the business simulation, followed by a post-task questionnaire.

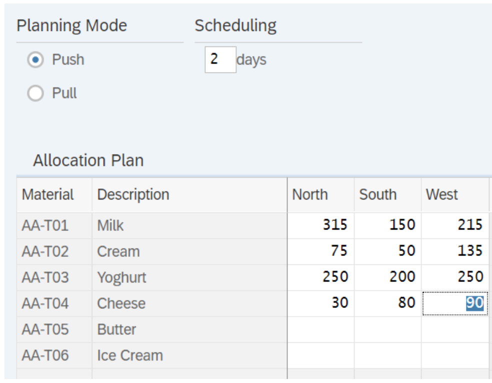
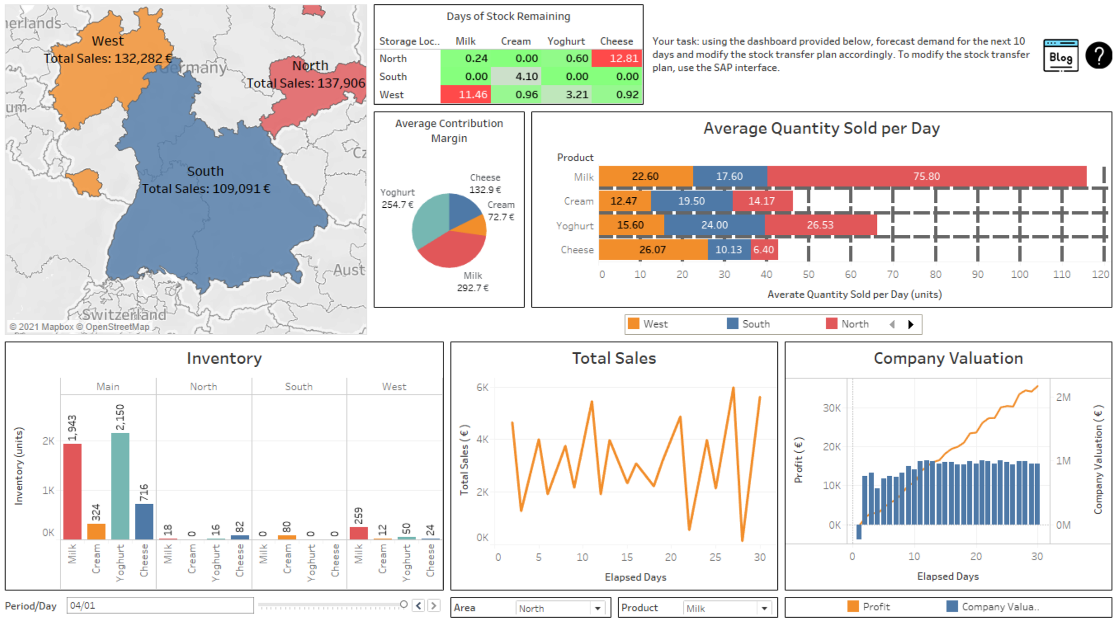


Figure 3. SAP Fiori Interface for Planning Stock Transfers

We used a between-subjects design with three conditions, and participants were randomly assigned 1 of the 3 conditions. Condition 1 corresponded to the Control group (n=22) and were not exposed to any of the nudges. Participants in Condition 2 (n=20) and 3 (n=22) were exposed to the social and warning nudge, respectively.

3.4.4 Experimental Stimuli

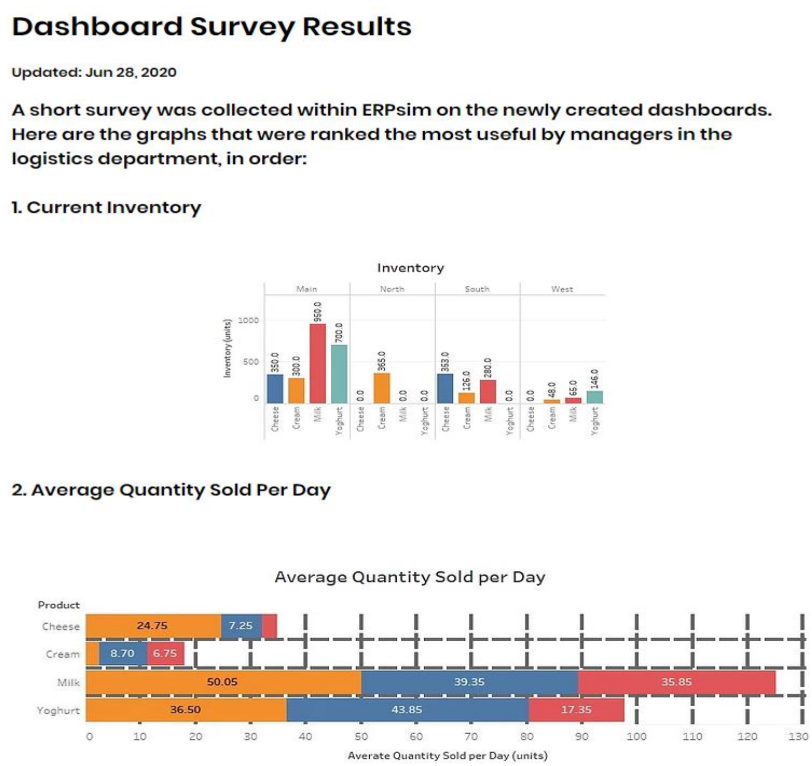
The experimental task builds upon the work by Demazure et al. (2019) and Lafontaine et al. (2017) and uses ERPsim (ERPsim Lab, Montréal, Canada). ERPsim is a realistic business simulation where students are required to use a real-life ERP based on SAP HANA S/4 (SAP, Waldorff, Germany) to manage a fictional business (Léger, 2006; Léger et al., 2007). Participants are tasked with playing the logistics scenario and are instructed to maximize sales by managing stocks in three different regions. As per Cronan et al. (2012), the scenario is played for a total of 2 rounds, each lasting approximately 8 minutes each. Participants must decide, based on the presented information, how much of each product to send to each of the three regions (Angolia, 2017). All participants played with the same parameters. Figure 3 shows the SAP interface participants used.



*Participants used this dashboard to create their stock transfer strategy within SAP. Useful graphs consisted of (1) Days of Stock Remaining, (2) Average Quantity Sold per Day, (3) Inventory and (4) Total Sales. Useless graphs consisted of (5) Average Contribution Margin, (6) Regional Sales (map) and (7) Company Valuation.

Figure 4. Tableau Dashboard

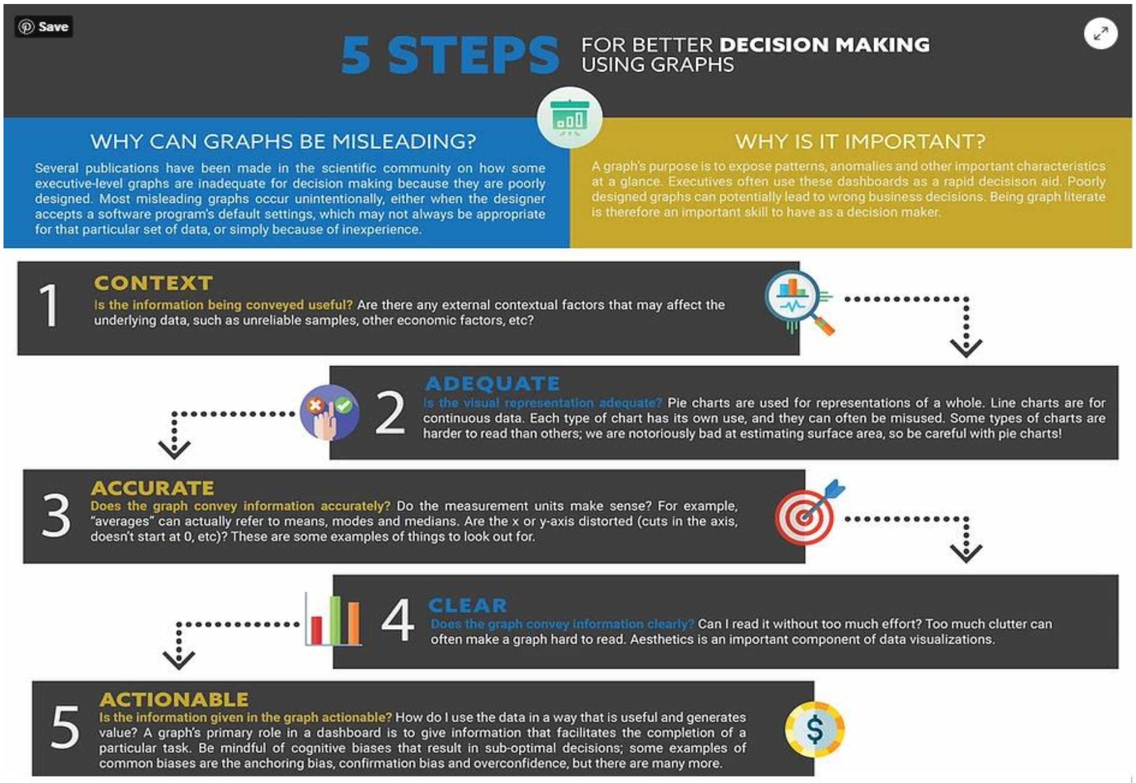
Building on Labonte-LeMoyne et al. (2017), decisions were based on a SAP HANA and Tableau (Tableau Inc, Seattle, US) dashboard with information such as Sales Per Region, Contribution Margin, Average Sales per Day, etc. in order to help them in their task, for a total of 7 graphs. Graphs were purposefully designed so that some are useful while others are not. A graph is useful if it contains information that is actionable within the context of the simulation, whereas it is useless if it contains superfluous information. An example of a useful graph is the average quantity sold per day, since it allows players to infer market preferences. An example of a useless graph is the aggregate sales per region; while it tells players which regions are more profitable, players do not know which products are selling better or worse in that particular region. In total, we designed 4 graphs meant to be useful, and 3 meant to be less useless. Figure 4 shows an example of the dashboard presented to the participants. All participants used the same dashboard.



*Graphs were ranked in order of importance as follows: (1) Inventory, (2) Average Quantity Sold per Day, (3) Days of Stock Remaining, (4) Total Sales, (5) Regional Sales , (6) Company Valuation, (7) Average Contribution Margin

Figure 5. Social Nudge

Participants in the Control group were immediately presented the dashboard, while the Condition 2 and Condition 3 group were exposed to nudges via the form of a short message presented in a blog format, embedded on their dashboards. Participants were asked to read the messages before accessing the dashboard. They were able to access the message at any time via an icon on the top right corner of their dashboard during the game. The different messages corresponding to Condition 2 and 3 are presented in Figures 5 and 6, respectively.



The nudge warns users that graphs can be potentially misleading and what consequences can arise from using bad graphs. 5 short steps are then provided to encourage the participant to be vigilant. The steps essentially remind participants that graphs should convey useful information in a easily readable format, that is actionable.

Figure 6. Warning Nudge

3.4.5 Operationalization of the Variables

Since all participants played 2 rounds of the game, we created a binary variable, reported as *dRound* (0 for Round 1, 1 for Round 2) to control for learning effects that may have occurred from Round 1 to Round 2.

We created 2 binary variables for the control and social nudge group, with both variables having a value of 0 for the warning nudge condition. The control group corresponds to condition 1 and will be reported as *Control*. The nudge type was manipulated between subjects by showing them either the social nudge or the warning nudge.

The social nudge uses peer comparison and ranks in order of importance the 7 graphs that other managers within the participant's department used to make their decisions during the game, with the higher ranking corresponding to graphs that are more useful. The social nudge is represented by condition 2 and will be reported as *Social*.

The warning nudge reminds the user of consequences of interpreting graphical information without much thought, and that some information may not be as useful as they think. We also provide 5 short steps to help users make better decisions when interpreting graphs. The warning nudge is represented by condition 3 and will be reported as the variable *Warning*.

To gauge the effectiveness of our nudges, we measured in-game performance and decision confidence as our dependent variables.

The in-game profit is the net profit in euros after 2 rounds of the logistics game. The simulator logs profit for each virtual day that passes within the simulation and allows us to extract this data to an Excel spreadsheet. A prior study using ERPsim has used this approach to measure in-game performance (Demazure et al., 2019). This variable will be reported as Profit.

The decision confidence was measured by asking the participant, after each round of the ERPsim game, how confident they were that their stock transfer plan would be successful in terms of performance. Decision confidence was measured with a 1-item, 7-point Likert scale. This variable will be reported as Confidence.

The 2 hypothesized moderator variables were self-efficacy and self-perceived experience with ERPs, and were collected at the beginning of the experiment via a survey. Refer to Appendix B for the items.

Task Self-Efficacy (TSE) was measured with a 7 item, 6-pt Likert scale, based on the Short Graph Literacy (SGL) scale (Garcia-Retamero, Cokely, Ghazal & Joeris, 2016). The items asked how confident the participant was at working with and interpreting various types of graphs. This variable will be reported as TSE.

Self-perceived Experience was measured with a single item, 5 point Likert scale, asking participants to rate their level of experience with an ERP from none (1) to significant (5). This variable will be reported as Exp.

3.4.6 Analysis

The chosen statistical tool was Stata 16.1 (StataCorp, Texas, USA). Linear regression models were run using Stata for each of the response variables. Following Hayes' (2017) recommendations, we use a moderated regression analysis to test our hypotheses by estimating 2 regression models, one excluding the interaction terms and one including them. For all models, we used Warning as our reference group. A series of post-hoc F-tests were done to test the differences between *Social* and *Control*. We also calculated and tested the difference in R^2 between models to determine the presence of moderation effects.

3.5 Results

3.5.1 Descriptive Statistics

Descriptive statistics for each variable are shown in Table 4. The skewness and kurtosis for TSE fell outside of values indicating normal distribution (skewness = -1.16, kurtosis = 5.7). However, we did not normalize this variable due to the log and square root transformation resulting in a higher skewness and kurtosis, and because the range of this variable was relatively small (min = 2.9, max = 5.7). A correlation matrix can be found in Appendix A.

The task self-efficacy scale was reliable at a Cronbach's Alpha (CA) of 0.75. As a manipulation check for our designed graphs, we asked 8 experts with extensive experience in playing ERPsim games to rate the graphs from a scale of 1 to 7, from useless to useful. We then calculated the inter-rater reliability. The reported ICC estimate was 0.95, indicating excellent inter-rater reliability (95% CI [0.87, 0.99], $p < 0.001$), which confirms that our graphs were designed adequately.

3.5.2 Main Effects of the Regression

In order to test H1 to H6, we estimated a linear regression model for each response variable without any interaction terms. These models included the condition groups, TSE and Exp as antecedent variables. The results of the first regressions can be found in Table 5. There were no significant differences between the in-game performance and decision confidence between any of the three experimental groups. H1 to H6 are therefore not supported.

	mean	std. Dev.	skewness	kurtosis
Control*	0.344	0.477	-	-
Social*	0.313	0.465	-	-
Warning*	0.344	0.477	-	-
TSE	4.880	0.485	-1.156	5.716
Exp	3.813	0.954	-0.494	2.829
Profit	13757.38	3639.20	0.697	2.974
Confidence	4.703	1.245	-0.728	2.938

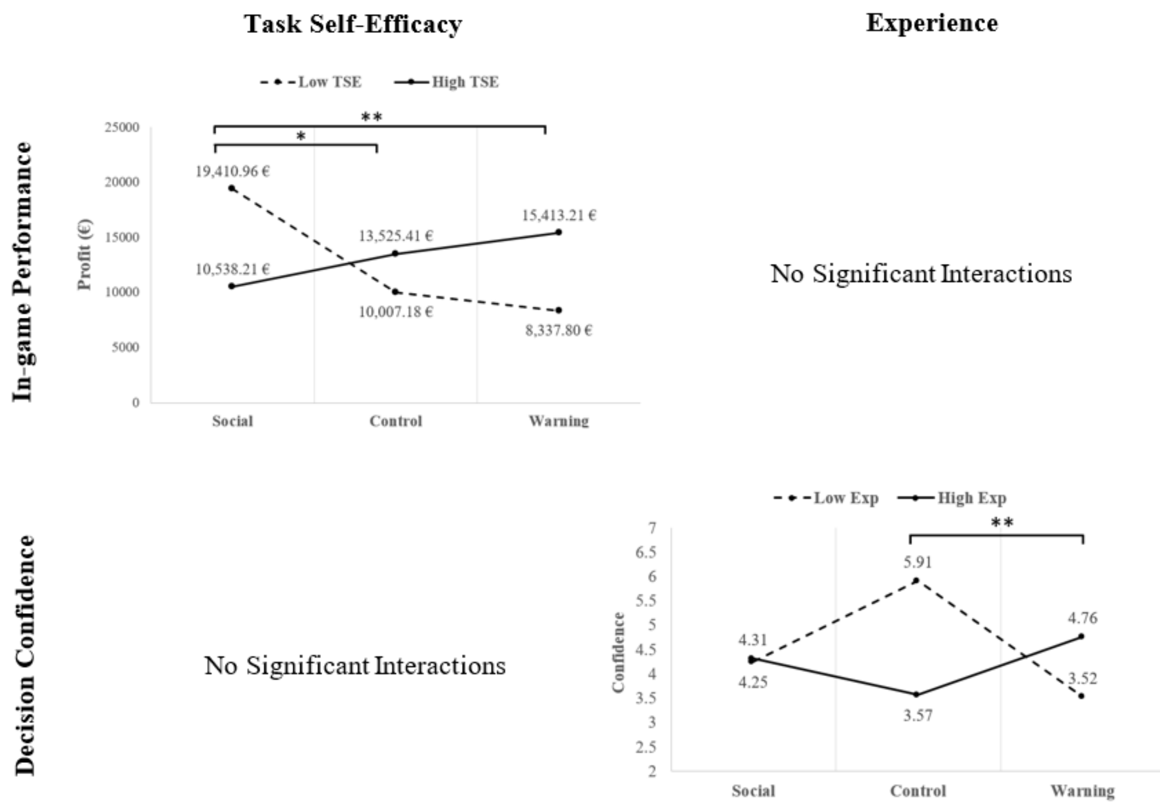
*Binary variables

Table 4. Descriptive statistics

	DV:	Profit	Profit	Confidence	Confidence
		reg1	reg2	reg1	reg2
dRound	Coeff.	-1855.87	-1855.87	-0.75	-0.75
	s.e.	403.10	409.87	0.16	0.16
Control	Coeff.	-825.03	3766.82	-0.14	6.78
	s.e.	866.40	7304.40	0.32	3.43
Social	Coeff.	-476.22	**29621.91****	-0.14	3.22
	s.e.	1070.59	8825.20	0.29	3.05
TSE	Coeff.	339.28	**2526.93***	0.31	**0.72***
	s.e.	744.55	1117.67	0.31	0.30
Exp	Coeff.	-458.28	-392.38	-0.12	0.31
	s.e.	413.47	589.08	0.16	0.21
Control*TSE	Coeff.	-	-1270.42	-	-0.72
	s.e.		1291.90		0.61
Social*TSE	Coeff.	-	**-5695.77****	-	-0.45
	s.e.		1912.54		0.51
Control*Exp	Coeff.	-	416.21	-	**-0.90****
	s.e.		836.75		0.34
Social*Exp	Coeff.	-	-532.72	-	-0.30
	s.e.		893.26		0.32
_cons	Coeff.	15209.35	4361.52	4.13	0.45
	s.e.	4115.19	5800.18	1.79	1.80
Pairwise Tests (post hoc)		Control – Social = 0 F(1,63) = 0.11 Prob > F = 0.7384	**Control*TSE – Social*TSE = 0*** F(1,63) = 10.49 Prob > F = 0.0107 -------------------------------- Control*Exp – Social*Exp = 0 F(1,63) = 1.12 Prob > F = 0.2940	Control – Social = 0 F(1,63) = 0.00 Prob > F = 0.9872	Control*TSE – Social*TSE = 0 F(1,63) = 0.16 Prob > F = 0.6924 ------------------------------- Control1*Exp – Social*Exp = 0 F(1,63) = 2.82 Prob > F = 0.0982
N		128	128	128	128
F		4.85	6.5348	5.3904	5.4010
r2		0.0914	0.1808	0.1177	0.2022
r2_a		0.0541	0.1183	0.0815	0.1413
p		0.0008	0.0000	0.0003	0.0000

Note: Baseline for the regressions is Warning
Note: * p < 0.05, ** p < 0.01

Table 5. Hierarchical Regressions for Profit and Confidence



Note: * = p < 0.05, ** = p < 0.01

Figure 7. Interaction Effects between Dependent Variables and Moderator Variables

3.5.3 Moderation Effects of the Regression

To test H7 to H14, a second set of linear regression models were estimated. The second models contain the variables in the first model as well as products involving the type of nudging with *TSE* and *Exp*. The results of the second regressions can be found in Table 6. Figure 7 represents graphically the moderation effects of *TSE* and *Exp* on the predicted values of the dependent variables.

First, let us look at decision performance. The difference in adjusted R^2 between the 2 models for decision performance is 0.0894 and was significant ($p < 0.05$), indicating the presence of a moderation effect. Upon closer examination, based on the regression and post-hoc test, we only found TSE itself ($p < 0.05$) and its two interaction terms to be significant. There was a significant difference in decision performance when comparing the Control group to the Social group, and when comparing the Social group to the Warning group, taking into account TSE. Therefore, there is support for H7 and H8, but not H9 and H10. Whether participants were nudged or not, and the type of nudge appears to have had different effects on performance, depending on the participant's TSE. Among those with relatively low TSE, the social nudge helped the most with in-game performance when compared with the control group ($F < 0.05$) and the warning nudge ($p < 0.01$). The warning nudge, on the other hand, has a larger positive effect on performance in the group with higher TSE when compared with the social nudge. The comparison was not significant between the warning nudge and the control group. The social nudge seems therefore more beneficial on performance for participants with low TSE, whereas the warning nudge has greater impact on participants with higher TSE.

Then, let us look at decision confidence. The difference in adjusted R^2 between the 2 models for in-game profit is 0.0845 but the difference was non-significant ($p > 0.10$). However, we observed that the non-significant difference in R^2 between models is due to most of the interaction terms being insignificant, save one. Upon closer examination, we found that only Exp had a moderation effect. However, only the comparison between the Control group and the Warning group was significant, lending support to H14, but not H10, H11 or H13. Whether the participant was nudged or not appears to have had different effects on decision confidence based on their level of experience, but this effect was not observable between the types of nudges. Among those with little experience with ERPs, the warning nudge had a negative effect on confidence ($p < 0.01$), when compared with the Control group. As experience increases, the effect is reversed; the effect of the warning nudge becomes positive. A summary of all the hypotheses and the results are provided in Table 6.

Research Question	Hypothesis	Supported?
RQ1	H1: The social nudge will positively impact decision performance	No
	H2: The social nudge will positively impact decision confidence	No
	H3: The warning nudge will positively impact decision performance	No
	H4: The warning nudge will positively impact decision confidence	No
RQ2	H5: The social nudge will have a greater positive impact on decision performance when compared with the warning nudge	No
	H6: The social nudge will have a greater positive impact on decision confidence when compared with the warning nudge	No
RQ3	H7: Task Self-Efficacy moderates the relationship between decision performance and social nudges, such that the lower the level of TSE, the more positive the effect of the social nudge	Yes
	H8: Task Self-Efficacy moderates the relationship between decision performance and warning nudges, such that the higher the level of TSE, the more positive the effect of the warning nudge.	Yes
	H9: Task Self-Efficacy moderates the relationship between decision confidence and social nudges, such that the lower the level of TSE, the more positive the effect of the social nudge.	No
	H10: Task Self-Efficacy moderates the relationship between decision-confidence and warning nudges, such that the higher the level of TSE, the more positive the effect of the warning nudge.	No
	H11: Experience moderates the relationship between decision performance and social nudges, such that novices will benefit more from this nudge than will experts.	No
	H12: Experience moderates the relationship between decision performance and warning nudges, such that experts will benefit more from this nudge than will novices.	No
	H13: Experience moderates the relationship between decision confidence and social nudges, such that novices will benefit more from this nudge than will experts	No
	H14: Experience moderates the relationship between decision confidence and warning nudges, such that experts will benefit more from this nudge than will novices.	Yes

Table 6. Summary of Hypotheses and Results

3.6 Discussion

There was no evidence that the nudges were effective in changing behavior, since no difference in the dependent variables were observed between groups. These are examples of nudges that fail; reviews by Hummel and Maedche (2019) and Caraban et al. (2019) found that only 62% and 66% of nudges were successful, respectively.

Caraban et al., (2019) found that nudging effectiveness is more dependent on its implementation and context, rather than nudge type. A possible explanation for our results is that our experiment dealt with a more complex task than prior studies testing social and warning nudges. Participants also played for a very short amount of time and were still familiarizing themselves with the task. Effort inducing interventions often take time and practice to understand and apply, as opposed to nudges that target unconscious processes (Hertwig & Grüne-Yanoff, 2017).

One explanation for the failure of the social nudge is the low social cohesion; the nudge used a fictional group of managers from a fictional organization as the social comparison. The closer and more relatable the point of comparison, the stronger the effect of the social norm (Kretzer & Maedche, 2018). Social norms are only effective if the individual actually cares about them, which may not have been the case in our study.

One explanation for the failure of the warning nudge is that the information was too complex to process, causing participants to discount the warning (Sunstein, 2017). Studies show that nudges that are more general are harder to understand and to apply (Junghans et al., 2015; Weaver, 2006). The information in the warning nudge was rather vague, as we aimed to engage reflection and not simply give out the answers. Additionally, warnings that remind of the consequences can have adverse effects by creating anxiety and consequently freeze their decision-making process, resulting in little to no change in behaviour (Sunstein, 2017).

Our findings indicate that simple, homogeneous nudges may not be effective in a complex enactive situation. Individual differences are important when designing digital nudges in a EUT context. Indeed, a review by Daamgard and Nielsen (2018) concluded that not every intervention will be able to produce positive effects for everyone; untargeted interventions are rarely effective. Wood et al. (1975) found that scaffolding was the most effective when the assistance was matched with the learner's needs.

In general, highly self-efficacious participants derived more benefits from the warning nudge than low self-efficacious participants in terms of in-game performance, whereas the social nudge had the strongest effect for low self-efficacious participants. We suggested that social nudges would have a bigger impact the lower the users' self-efficacy, as they would look to other people's actions to make their decisions, more so than highly self-efficacious users due to their need for more directed assistance (Margolis & McCabe, 2005). Individuals with higher self-efficacy also tend to be more resilient when faced with frustration, expend more effort and have more effective problem-solving strategies (Cherian & Jacob, 2013). Self-efficacy has also been shown to positively impact motivation to learn (Tai, 2006). The more complex information contained in the warning nudge may have deterred lower self-efficacious individuals from expending effort in understanding the contents of the warning, whereas higher self-efficacious individuals had an easier time assimilating, understanding and applying the information given to them when playing a simulation. Our findings imply that for learners with a low level of self-efficacy, nudge designers should include information that is easy to read and understand.

We found that more experienced participants generally benefit more from the warning nudge than do novices. This is observed in the participant's confidence levels; when compared with the control group, the warning nudge had a positive effect on confidence for experts, but a negative effect for novices. One possible explanation for this reversal effect is that more experienced participants had more knowledge about the task at hand due to prior experience and were able to make sense of the warning and follow the steps within the nudge. People who have more experience usually have the cognitive skills and resources to benefit from information exposure (Perkins & Rao, 1990).

Non-experienced participants, however, could have been further stressed by the warning nudge as they did not know what to make of it. Consequently, their confidence levels dropped. This shows that when reminding users of consequences, it is important to design the message in a way that is understandable and that does not generate anxiety, especially for lesser experienced users. As explained earlier, the warning nudge could have created some anxiety among the participants, and this was exacerbated for those with low experience.

The results with task self-efficacy and experience are supported by other works that found or believe that personalized nudges could be more beneficial (Damgaard & Nielsen, 2018; O'Connell & Lang, 2018; Brown, Schiltz, Derry & Holman, 2019; Peer et al., 2019). Nudges offering more direct assistance, such as the designed social nudge, could be delivered to novices or low self-efficacious individuals, whereas more complex nudges, such as the designed warning nudge, would have larger benefits for experienced or higher self-efficacious individuals. As experience and self-efficacy can be improved during a training program, this type of personalized nudging could also be tied to the progression of learners during the phases of a program.

3.7 Conclusion

This study contributes to the literature by being among the first to research digital nudging in an EUT context using business simulations and attempts to investigate the viability of nudges as it relates to learning in an enactive end-user training setting.

We attempt to paint an initial picture of nudging in a digital setting using social and warning nudges and the psychological mechanisms behind these nudges. Our findings indicate that simple nudges may not be enough to influence behavior in a complex problem-solving situation, and that digital nudging is not a teaching replacement. Nudging is certainly not a silver bullet to combat the cognitive biases that afflict us. However, self-efficacy and prior experience were found to play moderating roles in the relationship between the type of nudging and learning outcomes. This study contributes to the theoretical understanding of nudge mechanisms, as few nudging studies have attempted to incorporate individual characteristics. Our findings show that individual characteristics can affect how someone responds to nudging in a enactive problem-solving context. Our study also has interesting managerial implications; complemented with proper scaffolding techniques, nudging could act as helpful tools to influence EUT outcomes. Nudge and EUT curriculum designers could learn from our "failed nudges" and move towards interventions that are more effective, by adjusting the information within the nudge and personalizing the interventions based on individual characteristics.

We observed several effects that were significant at the 10% level. Using a non-convenience and a larger sample size would allow us to better understand the effects of interaction between task self-efficacy, experience and the type of nudge. Future studies could attempt to replicate this study with a larger sample size or in a different context and verify whether TSE and experience maintain their moderation effects. Additionally, a coaching system that would offer personalized advice would be interesting to explore in an enactive EUT context. For example, Brown et al. (2019) found that tailoring nudges based on behavior, in addition to considering motivational factors is effective at impacting behavior.

Another limitation of this study is that we only controlled for learning effects, and with the moderator variables. Numerous studies have identified factors that influence learning, such as learning style, learning engagement, cognitive engagement and many more. Future studies should attempt to incorporate these variables.

Future studies could expand on this study by incorporating physiological data, such as eye tracking, as self-reported measures are not always reflected in behaviour. Another avenue of research involves studying the digital medium in which nudges are delivered. We used a blog format, but more research is required on what type of interface is optimal in delivering these types of nudges. There is also a vast number of options of nudges that have yet to be studied in this context.

3.8 References

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3.9 Appendix A

	dRound	Control	Social	Warni-ng	TSE	Exp	Profit	Confidence
dRound	1.000							
Control	0.000	1.000						
Social	0.000	-0.488***	1.000					
Warning	0.000	-0.524***	-0.488***	1.000				
TSE	0.000	-0.099	0.161	-0.058	1.000			
Exp	0.000	0.004	-0.080	0.074	-0.127	1.000		
Profit	-0.256**	-0.083	0.009	0.075	0.061	-0.122	1.000	
Confidence	-0.303***	-0.039	-0.002	0.041	0.127	-0.100	0.079	1.000

Bilateral Test (level of significance; * p <= 0.05; ** p <= 0.010; *** p<= 0.001)

N=128

Table. 7 Correlation Matrix

3.10 Appendix B

Exp - How much experience with Enterprise Resource Planning (ERP) systems do you have?

A great deal (5)

A lot (4)

A moderate amount (3)

A little (2)

None at all (1)

TSE - Please select the response that reflects how you feel towards these statements

	Very Bad (1)	Bad (2)	Moderately Bad (3)	Moderately Good (4)	Good (5)	Very Good (6)
How good are you at working with bar charts? (1)	○	○	○	○	○	○
How good are you at working with line plots? (3)	○	○	○	○	○	○
How good are you at working with pie charts? (4)	○	○	○	○	○	○
How good are you at inferring the size of a bar in a bar chart? (5)	○	○	○	○	○	○

How good are you at determining the difference between 2 bars in a bar chart? (6)	○	○	○	○	○	○
How good are you at projecting a future trend from a line chart? (7)	○	○	○	○	○	○

	Strongly disagree (1)	Disagree (2)	Slightly Disagree (3)	Slightly Agree (4)	Agree (5)	Strongly agree (6)
Graphs are easier to understand than numbers	○	○	○	○	○	○
I often find graphical information to be useful	○	○	○	○	○	○
I believe in the saying "a picture is worth a thousand words"	○	○	○	○	○	○
I find graphs that are part of a story to be helpful when reading books or newspapers	○	○	○	○	○	○

Confidence - Please indicate to how you feel towards each of the statements presented below

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am confident that the stock plan I have set will work well	○	○	○	○	○	○	○

Chapter 4
Conclusion

The main objective of this thesis was to determine whether digital nudging could be an effective tool to enhance learning in a enactive training context. More specifically, we wished to investigate if digital nudging could impact skill-based and affective training outcomes. We used decision performance and confidence as a measure for the 2 aforementioned outcomes, respectively. Based on the literature, we also hypothesized that certain types of nudges could be more effective than others, such as social nudges when compared with warning nudges. We also hypothesized that individual characteristics, specifically prior enterprise systems experience and task self-efficacy would affect the effectiveness of the nudges.

First, a systematic review was done to identify research gaps on the topic of nudging in organizational or educational settings. Only 9 relevant empirical studies were found, indicating a lack of research within this field. We believe to be one of the firsts to study digital nudging as it relates to an enactive training context. The review also served to identify which types of nudge that could be potentially suited to our goals and experimental design.

Afterwards, a between subjects experiment was conducted in the summer of 2020 to test our hypotheses. 64 participants were recruited and compensated with a 30$ Amazon gift card. These participants played 2 rounds of a business simulation, ERPsim (ERPsim Lab, Montréal, Canada). The control group played without being exposed to the nudges, and both treatment groups were exposed to the social or warning nudge.

Finally, the resulting process of the thesis resulted in the redaction of two articles. This final chapter reiterates the research questions and the main findings of these articles. Then, we come back on the theoretical and practical contributions of this thesis, and discuss limitations and future studies.

4.1 Research Question and Main Findings

The thesis' main objective was to investigate the viability of nudges to improve learning outcomes in an enactive end-user training context. Our research questions were as follows:

RQ1. Can training outcomes be positively influenced by digital nudging in an enactive EUT context?

RQ2. What type of digital nudge is more effective at supporting training outcomes in an enactive EUT context?

RQ3. Are the effects of digital nudging homogeneous across learners?

In order to answer these research questions, several hypotheses were posited. The hypotheses and results can be found in Table 7.

The first article attempts to answer the research questions by reviewing past empirical studies. The reported effectiveness of nudges are mixed, but some studies within organizational and educational fields have demonstrated that some type of nudges can positively influence factors that impact learning effectiveness, such as engagement and performance. The literature also indicates that reflective nudges, nudges that trigger reflective processes, to be more common when the goal is to influence performance or learning effectiveness. Finally, social nudges were found to be the most common type tested, while other types, such as reminders, defaults, priming, precommitment and informational nudges, were only tested in one or two empirical studies. The first article therefore presents initial research opportunities into this topic and ties into the experimental study.

The second article attempts to answer the research question via an experimental study. To address the first and second research question, we use decision performance and confidence as measures to evaluate the effectiveness of nudging, and whether one type of nudge is more effective than the other. The third research question addresses the question of individual differences by taking into account prior enterprise systems experience and task self-efficacy in our analysis, allowing us to determine if these variables have an effect on decision performance and confidence.

Research Question	Hypothesis	Supported?
RQ1	H1: The social nudge will positively impact decision performance	No
	H2: The social nudge will positively impact decision confidence	No
	H3: The warning nudge will positively impact decision performance	No
	H4: The warning nudge will positively impact decision confidence	No
RQ2	H5: The social nudge will have a greater positive impact on decision performance when compared with the warning nudge	No
	H6: The social nudge will have a greater positive impact on decision confidence when compared with the warning nudge	No
RQ3	H7: Task Self-Efficacy moderates the relationship between decision performance and social nudges, such that the lower the level of TSE, the more positive the effect of the social nudge	Yes
	H8: Task Self-Efficacy moderates the relationship between decision performance and warning nudges, such that the higher the level of TSE, the more positive the effect of the warning nudge.	Yes
	H9: Task Self-Efficacy moderates the relationship between decision confidence and social nudges, such that the lower the level of TSE, the more positive the effect of the social nudge.	No
	H10: Task Self-Efficacy moderates the relationship between decision-confidence and warning nudges, such that the higher the level of TSE, the more positive the effect of the warning nudge.	No
	H11: Experience moderates the relationship between decision performance and social nudges, such that novices will benefit more from this nudge than will experts.	No
	H12: Experience moderates the relationship between decision performance and warning nudges, such that experts will benefit more from this nudge than will novices.	No
RQ3 (cont.)	H13: Experience moderates the relationship between decision confidence and social nudges, such that novices will benefit more from this nudge than will experts	No
	H14: Experience moderates the relationship between decision confidence and warning nudges, such that experts will benefit more from this nudge than will novices.	Yes

Table 8. Summary of Hypotheses and Results

Overall, the findings indicate that either nudge did not directly and significantly impact end-user skill-based or affective training outcomes. A possible explanation for these results is that the game was too short to see any significant improvements or degradation in performance or confidence. Interventions that are targeted at engaging reflective behaviour often take additional time in order to understand and apply and participants only played 2 rounds of the game (Hertwig & Grüne-Yanoff, 2017). Additionally, as mentioned in the literature review presented in Chapter 2, the success rate for nudges is only 62% (Hummel & Maedche, 2019). We also discussed publication biases within the first article, where some papers with unsuccessful nudges were not published, thus making the real success rate of nudges even lower than what is presented in the literature.

One explanation for the failure of the warning nudge is that it may have contained too much information, or was too complicated to understand in a short amount of time, resulting in participants ignoring the warning. Additionally, warnings can create extra anxiety or skepticism, causing individuals to freeze or slow down their decision-making process, resulting in little to no change in behaviour (Sunstein, 2016).

The results for the social nudge were surprising, as there is empirical evidence that similar nudges work rather well (O'Connell & Lang, 2018; Kretzer & Maedche, 2018; Lawrence et al., 2019). One possible explanation is the low social cohesion of the peer comparison point. In the experiment, the actions of fictional managers were made more salient, in the hope that participants would conform to the fictional managers' actions. However, social comparisons tend to work better when the point of comparison is relatable, or socially cohesive. Participants may not have cared about a group of fictional managers (Kretzer & Maedche, 2018). More research is required in order to understand why social nudges sometimes fail (John & Blume, 2018).

There could be a common reason for the failure of both nudges; the complexity of the task relative to the amount of assistance the nudge provided may have been too high, resulting in no differences in performance or confidence.

While the nudges did not have a significant direct effect on the end-user training goals, some moderating relationships were found. Task self-efficacy and experience are two individual characteristics that change the form of the relationship between nudging and end-user training goals. These moderating effects suggest that warning nudges that contain more general information were better suited for experts and highly task self-efficacious participants, whereas the social nudge, which contained more context-specific information, fared better with novices.

The literature suggests that specific information is generally easier to process and apply compared to more general, vague information (Perrenet & Groen, 1993; Dolan et al., 2012). It also suggests that in order for feedback to be perceived as useful, it must match the learner's current knowledge (Weaver, 2006). A possible explanation as to why the more general warning nudge fared better with experts is that they already possess mental models, knowledge and strategies related to the task at hand, allowing them to understand the contents of the nudge (Hung, 2001; Léger, Riedl et al., 2014). Novices, on the other hand, preferred more specific information that did not require previous knowledge to understand (Junghans et al., 2015).

As task self-efficacy in this study was specifically related to the task at hand, i.e. graph interpretation and analysis, participants who are highly self-efficacious were presumably more perseverant and effortful in their use of the information in the warning nudge to their advantage. Those with lower self-efficacy may have been more likely to disregard information that is complex, and therefore preferred the more directed assistance the social nudge provided (Bouffard-Bouchard, 1990).

4.2 Contributions

This thesis contributes to the gap in the literature and to our understanding of nudges in an organizational learning context, specifically within enactive situations. It presents an initial foray of research in nudging in end-user training contexts. Our results suggest that individual characteristics are important to consider when designing nudges that engage reflective thinking. Based on our findings, we also suggest that individualized interventions can be more effective than homogeneous interventions, which supports other works on this topic (O'Connell & Lang, 2018; Damgaard & Nielsen, 2018; Brown et al., 2019; Peer et al., 2019)

From a practical perspective, this thesis shows that digital nudges can be easy to implement, cost-effective interventions. Asides from a Tableau license, the digital nudges were all developed using free resources, such as Wix (Wix Ltd, Tel Aviv, Israel) to host the blogs that contained our nudges. Our work can also sensitize EUT curriculum designers of potential biases that can occur when using enactive teaching methods such as business simulations. Finally, for nudge designers or EUT curriculum designers who wish to incorporate digital nudging, we provided some recommendations for better nudging. We found that when it comes to affecting learning outcomes, nudges that attempt to engage reflection are more common, as self-reflection is a critical component in developing competencies. When designing the nudges, it should be taken into account that novices and low self-efficacious individuals will tend to do better with more directed, easier to understand information (social nudge) and are adversely affected by complex information. Experts and highly self-efficacious individuals on the other hand, seem to do better with more vague, but complex information. As such, we believe personalizing nudges could potentially lead to greater effects. As experience and self-efficacy can evolve along the course of a training program, the types of nudges could also be tied to each phase of a training program.

From a methodological perspective, this study was done during the 2020 COVID-19 pandemic, and shows that remote real-time data collection can be a practical approach. This research method removes geographical limitations and researchers can collect data from multiple countries. An interesting advantage to this method of data collection is the ability to explore cultural differences. It also shows that studies using ERPsim can easily be done remotely in a synchronous way, and is applicable in a real-life setting with employees in an organization. Another advantage of this method is the ease of recruitment; since the experiment can be conducted from the participant's homes and require minimal equipment, a relatively sizable amount of participants were recruited within a short amount of time.

4.3 Limitations

This thesis is not without its limitations. First, the short duration of the experimental study did not allow us to study the full potential effects of nudges. The ERPsim games are not designed to be played over such a short period of time, nor alone. Therefore, results from this study can only be marginally extended to real life settings where ERPsim is used as a training tool in commercial settings.

Second, there have been works showing many factors other than task-self efficacy and contextual expertise affecting learning effectiveness, such as perception of control (Léger, Davis, Cronan &

Perret, 2014) and different types of expertise (Cronan et al., 2012). We only controlled for learning effects that may have occurred between the 2 rounds that were played. There are also potential factors relating to the nudges that we did not control for, such as the different visual aspects between the design of the two nudges.

Third, this study lacked more robust manipulation checks. One example if this is that there were no attention checks on the nudges; a simple question at the end of the experiment asking about the content of the nudge could have served as an attention check.

Fourth, the studied sample was fairly homogeneous in terms of characteristics; a majority of participants were students. Additionally, this did not reflect a real training environment, as collaborative learning is a big aspect of business simulation games such as ERPsim. Therefore, we are cautious in generalizing our results in other contexts.

Fifth, due to social distancing restrictions due to the 2020 pandemic, tools that are only usable in-person, such as eye-tracking, were no longer an option. This presented a problem as the initial plan was to investigate behaviour at a physiological level to answer calls for research using these tools. The findings would have been potentially more novel than what is presented in this work.

4.4 Future Studies

Based on our findings, we established that simple nudges are not sufficient for complex enactive tasks. However, we also show that individual differences, such as experience or self-efficacy, affects the relationship between the type of nudge and training outcomes. This brings up an important future research question: are personalized, targeted nudges more effective than non-targeted ones? As described by Meske and Potthoff (2017), designers should take an iterative approach to nudge design; tailoring the content of the nudge according to the user's individual characteristics would be a challenging, but potentially more effective method of designing impactful nudges. However, more research is also required in understanding the factors impacting learning in enactive scenarios, that should be considered in designing nudges.

One of the limitations discussed was the short duration of the experiment. Future studies should look at the effects of nudging over a longer period of time to allow a better control for learning effects. The Logistics game supports up to 12 rounds; participants could be made to play an additional 2 or 3 rounds, which should not add a significant amount of time to the experiment.

Additionally, while this experiment showed an asynchronous method of playing the ERPsim games, future studies could compare asynchronous and synchronous methods of playing. Future research questions on this topic could also show how group dynamics in end-user training impacts the effectiveness of nudges, as collaboration is an important aspect of learning (Hwang, 2018).

Future studies should integrate these various constructs for a more comprehensive framework. For example, as mentioned in the previous section, perception of control (Léger, Davis et al., 2014) and different types of expertise (Cronan et al., 2012) can come into play when it comes to learning effectiveness. Based on our last suggestions, using an experimental setup where more than 1 person is playing would introduce a competitive aspect to the simulation, which would allow us to study constructs such as risk propensity and teamwork.

Another interesting avenue would be to use eye-tracking to study the user's gaze to understand how they read the nudges and the dashboard, which could offer valuable insight on the different nudges' effects, and how individuals scan information relative to the complexity of the information within the nudge.

Finally, the methodological contributions show that running a synchronous ERPsim game is certainly feasible. Future studies could attempt to replicate an end-user training more accurately by leveraging ERPsim's certification programs; instructors could be recruited and trained remotely using this method, giving the results more external validity.

4.5 Closing Remarks

End-user training is one of the most important elements in IS acceptance. Fostering skill-based competencies and self-confidence in employees is essential if a business wants to leverage the capabilities of enterprise systems. Serious games for learning are a way for the end-users to develop these training outcomes in an engaging way, but these games usually generate higher cognitive load. This thesis found that simple, homogeneous nudges may not provide enough assistance to help learners in a significant way to overcome certain biases. However, we found that individual characteristics, such as self-efficacy and experience should be considered in designing better, personalized nudges that will hopefully have stronger effects. We hope that our failures can be a lesson to future researchers, and hope to stimulate research in employee experience in order to create better learning experiences.

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