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Nudges in Technology-Mediated Knowledge Transfer: Two Experimental Designs

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ABSTRACT

Recent advances in technologies now allow us to learn almost anything in virtual environments, be it via Internet forums or websites, telephone apps, video games, and many more. Such technology-mediated learning can be enhanced with the use of embedded nudges, i.e., devices in the architecture of choice to encourage (*nudge*) the users towards one choice rather than the other without limiting their freedom of choice. This paper presents an overview of how nudges can help improve knowledge acquisition, as well as a two ongoing projects. Ethical issues are also highlighted.

CCS CONCEPTS

• **Human-centered computing** → **Natural language interfaces**; **Sound-based input / output**; *Laboratory experiments*.

KEYWORDS

digital nudges, machine learning, multimodal sensors, second language learning

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1 INTRODUCTION

Nudges are a concept established by Thaler and Sunstein [73] and 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” [73, p. 6]. Nudges thus rely on cognitive biases, i.e., systematic deviations from rational judgment, to “trick” people into making the “right” choice.

A digital nudge, as any kind of nudge, is an almost imperceptible incentive in the design of a digital system to drive behaviour that

is supposed to improve personal or collective well-being. Sludges are mostly considered as a particular kind of nudges, which add friction to the decision-making process. At present, digital nudging mechanisms use familiar online technologies such as speech interfaces, chatbots, robots, video-games, etc. These mechanisms are used in several domains such as health and education.

In the ANR French chair HUMAAINE “Human-Machine Affective Interaction & Ethics”, we are carrying out research to audit and measure the potential influence of affective systems on humans and nudging system interactions and relationships in different domains such as education. In Mehenni et al. [63], we presented an experimental protocol during which children at primary school interact with a dialog system capable to influence through indirect suggestions which can affect behavior and decision making. First results highlighted that the conversational agent and the robot are more influential in nudging children than a human interlocutor. In Mehenni et al. [62], we described an automatic user states’ detection experiment based on paralinguistic and linguistic cues for driving automatic nudging system.

The present paper focuses on the usage of nudges in master and knowledge transfer using technological devices. The aim of the paper is to show the extent of current research on nudges in learning a second language and highlight the questions that research on nudges in educational technologies has to tackle. What we call “knowledge transfer” here refers to the operation consisting of providing information to learners so that this information becomes knowledge.

We present two experimental protocols designed for nudging students who learn a second language: One is related to prompted speech in the ANR project LeCycl and the second one, the French BPI project EduWinky, uses human-machine interaction with a robot. LeCycl is a framework to observe how learners acquire knowledge, their behaviors being measured by sensors and utilized to select how to nudge them. EduWinky aims to test children learning English during a series of exercises with the support of a robot. This will allow us to establish how the gamification of learning through the interaction with a robot dispensing nudges can enhance the children’s performance and will to keep exercising.

The paper is organized as follows. In Section 2, we provide a typology of nudges usable in knowledge transfer, along with a literature review on their efficiency and limitations. In Section 3, we present our two experimental designs. Finally we conclude in section 4 by raising awareness on the fact that digital nudge systems in education highlight some ethical issues.

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2 NUDGES IN KNOWLEDGE TRANSFER AND ACQUISITION

In this section, we provide an extensive overview of the nudges usable in knowledge transfer by educational platforms, be they websites, apps or video/audio games. We also provide a detailed account of their efficiency in knowledge acquisition by the learner and of their general, technical, and ethical limitations.

Damgaard and Nielsen [26], in their meta-analysis on nudges in education, list all nudges used in education policies and classroom operations. They divide nudges into 5 types: "pure" or non-educational nudges, educational nudges, boost interventions, motivational nudges, and brief psychological interventions. In the following, we use the same typology, except we regroup the last three types under the label "motivational nudges". We present exclusively nudges that apply to educational technologies and show how they can be implemented.

2.1 "Pure" or non-educational nudges

"Pure" or non-educational nudges can be divided into two classes.

On the one hand, they can work sub-consciously, in which case they target systematic cognitive biases, such as the default bias, loss-aversion, etc. through subtle changes to the decision environment. As such, they invite passive decision making and are thus better for situations of high cognitive load such as learning [81] but could be considered as less ethical (review in Weijers et al. [81, p. 895]). However, although transparency acts as an "ethical filter" [44, p. 247], no research, to the best of our knowledge, has been conducted on the effect of nudge transparency in education.

We have identified 4 such "discrete" non-educational nudges that can apply to educational technologies:

- **Default nudges** consist of using a default setting that is considered as more efficient for the learner, but can still be changed if the learner wishes [26]. This nudge takes advantage of the default bias, i.e., the inherent preference of human beings to keep things as they are [47]. This nudge has been shown to be effective in cases of student enrolment [11, 60], but was never tested for learning in particular. In the case of educational platform, it could easily be implemented, as software design and architecture heavily rely on default settings.
- **Framing** consists of framing the question or inquiry in a way that favors the right answer [75]. It has however been shown to have no significant effect in most of the studies conducted [2, 36, 54, 55, 59, 61, 77].
- **Peer-group manipulation** restructures the choice environment to ease and encourage peer interaction. This may help improve the sense of social belonging, strengthen or create social norms of effort provision, or improve knowledge transfer through study groups. This type of nudges relies on social image concerns (and subsequent social pressure). However, research has provided either negative [20, 58, 70] or marginally positive results [19, 67] with regard to their efficiency.
- The **Endowment effect** [65] consists of generating a sense of ownership, identification with learning material supposedly improving the degree of engagement, for instance by

providing the learners with opportunities to personalize their materials. This again relies on loss-aversion [36], as the learner will be attached to their material and less inclined to neglect it. This type of nudge has, to the best of our knowledge, never been proved to be efficient, but could easily be implemented in educational platform with personalized avatars or features.

On the other hand, non-educational nudges can also be less hidden and encourage people to use them in specific failure-risk situations. In this sense, they provide either changes or additions to the decision environment and as a result may change behaviour through better active or passive decision-making.

We identified 3 such nudges useful for technology-mediated education:

- **Deadlines** consist of proposing a deadline, which can be optional or rewarded. Some studies have shown the efficiency of deadline nudges [4] while others have found negative effects [17]. It would therefore be very valuable to test how such deadlines are efficient in a virtual environment.
- **Goal setting** consists of setting a goal for a particular activity. Results on its efficacy are mixed [23, 56]: To work, goals must be self-set and not too high [32, 33, 76]. Again, it would be interesting to test such a nudge on a learning platform.
- **Reminders** consist of sending regular reminders, i.e., remind of already known information, but also of sending regular notifications, i.e., transmit novel information, to implicate the students. Studies on this subject have found either positive [21, 22], mixed [13, 52] or no effect [66, 68]. Since push notifications are a core aspect of most phone apps, it would be interesting to see whether such notifications can really implicate learners more, and in what limits.

It is notable that these three nudges result in helping learners plan how to complete their assignment, which has been shown as the most useful type of nudges in a study dedicated to nudges in self-directed learning [38].

2.2 Educational nudges

Nudges that are specifically educational are defined as such because they aim for persistent behavioral change [81], in our case, information retention, through active decision making via additions to the choice environment, in our case, the learning environment. They are often conscious but may also work subconsciously, e.g., by making certain information more salient. These nudges rely on memory of past utility [3], self-perception [10], and repetition [9, 45].

Two educational nudges can be listed here:

- **Informational nudges** consist of adding small pieces of information to underline the importance of a topic. These nudges have proven efficient [8, 15, 29, 59, 69] and should therefore be tested on educational platforms, for instance by implementing pop-up windows with relevant pieces of information.
- **Assistance** consists of providing regular and easy assistance. Its efficiency was never tested for learning. It would be interesting to test whether accessible how-to pages or assistance

bots can improve the learning experience on an educational platform.

2.3 Motivational nudges

What we call here "motivational nudges" actually regroups what Damgaard and Nielsen [26] call "boost interventions", "motivational nudges", and "brief psychological interventions". They are detailed below:

- **Boost interventions** deliberately aim at improving active decision-making by teaching individuals about cognitive biases hindering their experience and providing counsel to tackle these hindrances. In the context of education, teaching students about particular skills (motivation, grit, etc.) generally has a positive effect [1, 12, 28, 64, 72] vs [31]. Such boost interventions could easily be implemented as notifications or as pop-up windows in educational platforms, and their efficiency should thus be tested.
- **Motivational nudges** *per se* consist of adding information or rewards that consciously or sub-consciously motivate individuals to change their behaviour. This category of nudges includes:

Social comparison nudges, a particular kind of informational nudges since it consists of providing the learner with information that facilitates comparisons with other learners and bring them to wish for adherence to what they believe is the social norm. Among these nudges, several have been found to be effective, such as classical social information nudge [24], relative grading, especially for boys [46] vs [25], relative performance feedback [7, 27, 59, 74] provided there is time [35] but which can sometimes backfires [6]. Others, such as relative performance feedback, have proven to have a negative effect [18, 78]. In any case, it would be interesting to test whether such nudges can influence a learner's experience or performance on an educational platform, for instance by measuring the effect of ranking users of the platform, either anonymously (learners only know their own rank) or non-anonymously (learners also know the other learners' ranks, or the rank of the learners from their network).

Nudges using extrinsic motivation, which explicitly link rewards to the desired behaviour. Positive effects have been found for non-monetary rewards [43, 46, 55], especially for children [43, 55]. However, these nudges seem to have mixed effects on student performance [37, 42, 48, 78]. It would be interesting to test whether educational platform can take advantage of devices already used in video games such as in-game currency.

- **Brief psychological interventions** target students' mindsets and beliefs with the aim of creating a self-reinforcing but subconscious improvement in motivation and achievement. Unlike 'pure' nudges, the goal of motivational nudges is to influence behaviour not only at a given moment during the learning experience but, like educational nudges, to result in long-term information retention or skill acquisition. They include:

Social belonging, which is supposed to strengthen the learner's sense of belonging to the community of learners

and to address their insecurities about their own abilities [38, 51, 79, 82, 85]. Walton et al. [80] found positive effects but Broda et al. [16] found no effect. It would therefore be interesting to test whether such communities can be created in online educational platforms, and to what extent they improve the learner's experience and performance.

Identity activation, which provides information on personal or academic struggles of regarded personalities to create a sense of identification and motivate the learner to overcome their own struggles. This type of nudges has proven efficient [39, 57, 84] and could easily be tested in a virtual environment, for instance by measuring whether such information in a pop-up window actually increases learners' motivation (that could be measured by the duration and regularity of learning sessions on the platform) and subsequent performance (that could be measured by tests).

Mindset nudges, which consist of shifting the learners' opinion on learning and personal limitations, e.g., by teaching learners that intelligence is malleable rather than fixed. This type of nudges has showed positive effects on academic behaviour [5, 14, 40, 83] and could therefore, again, be tested in pop-up informational windows.

2.4 Intermediary conclusion

In this section, we have shown that several nudges can actually apply to knowledge transfer via digital educational platforms. Their efficiency was only tested in offline experiments, in particular in the framework of school or university students. In this framework, it has been shown that the efficiency can vary from nudge to nudge.

On the one hand, some non-educational nudges such as framing and peer-group manipulation, have been tested for their effect on learning, but have shown little efficiency in offline learning, and there is little hope that they would improve significantly online learning. They should still be tested, but probably not in priority.

On the other hand, default nudges, informational nudges, boost interventions, most social comparison nudges, identity activation nudges, and mindset nudges have all proven rather unequivocally efficient. As such, they should definitely be tested in virtual learning environments. Other nudges, such as deadlines, goal setting, reminders, nudges using extrinsic motivation and social belonging have shown mixed results regarding their efficiency. These mixed results may be dependent on the environment itself, and it would therefore be important to test them in a virtual learning environment as well. Moreover, some nudges such as the endowment effect and assistance have not been tested for learning specifically, and should therefore be investigated in both non-virtual and virtual learning experiments.

One interesting point is that most of the nudges that show promise regarding the improvement of online learning are implemented in other online platforms. Default settings (and the possibility to change them) are a core characteristics of most, if not all, virtual platforms and devices, and reminders (or notifications) are dispensed by a large number of phone apps. The endowment effect is taken advantage of in video-games allowing the players to personalize their avatar or customize their virtual board. Social comparison nudges are used in video games allowing online rankings

with other players, or in commercial websites informing the users how many people have seen or bought the item. Websites also already use pop-up informational windows to display commercial ads. There is therefore no doubt that we have the technological means to implement such devices in educational environments to test their efficiency on the success on the learning process. In this paper, we specifically focus on two projects with nudging strategies.

3 TWO EXPERIMENTAL DESIGNS

In the present section, we present two ongoing projects that try and fill the void in current research on using nudges in the specific domain of educational technologies.

3.1 LeCycl

LeCycl is a trilateral research project between France (interdisciplinary laboratory of digital sciences (LISN)), Japan (Metropolitan University of Osaka) and Germany (German research center for artificial intelligence (DFKI)). The goal of the project is to accelerate and strengthen the learning cycle along three main stages: (i) identifying lacking knowledge (via text, audio and eye tracking), (ii) acquiring the identified missing knowledge or mastering new skills (via training and exercises) and (iii) transfer of the new knowledge to others (via discussions and presentations). For the perception and mastery stages, LeCycl teams gather measures of speech and text processing, as well as measures of a variety of behavioral features (attention, hesitations, voice tone, etc.) from different sensors (eye-tracker, camera, microphone, etc.) in order to analyze the students' emotional and cognitive states and understand their knowledge acquisition process. For the transfer stage, they use nudging strategies to guide the learning process and ensure effective knowledge transfer [7, 41]. For the time being, the project focuses mostly on the domains of second language learning and programming.

We are presenting here the research dedicated to learning English as a second language and how it can be enhanced with nudge strategies. Our team investigates cross-cultural and cross-linguistic features in English learning by native speakers of French and Japanese. The participants perform language tasks calling upon their knowledge of English, such as reading texts of different levels (in France) or both reading texts and deciphering images through a manga-type document (in Japan) [49]. The participants' performance is measured through verbal and non-verbal measures, such as the comparison of the participants' non-native realizations with canonical native pronunciation, or eye movements.

More precisely, Kobylanskaya [53] has built an experimental protocol for language learning involving 50 French speakers of English whose voice and eye movements have been recorded using the *Eye Got It* tool [34]. A joint analysis of eye-tracking and acoustic features will allow us to understand the participants' level of stress, comprehension, reading and learning strategies as well as pronunciation difficulties.

This information will then be used to implement nudging techniques adjusted on individual and cultural learners' characteristics during performance. Concretely, we will use machine learning techniques to create an experimental design where the detection of reading difficulties is countered with nudges. This will allow us to investigate how and how much various types of nudges help

participants improve their performance on the task. Jointly, we will evaluate the way the implementation of nudging strategies influences the learners' performance at all three stages cited above.

3.2 EduWinky

EduWinky is a project involving the French interdisciplinary laboratory of digital sciences (LISN) and two industrial partners, among which a company commercializing a small robot called Winky. This project also highlights the necessity to evaluate the ethical implications of nudge strategies, including in learning environments, so as to avoid addiction phenomena to a digital device, or discrimination due to nudges working better on one population than on another.

The project has two goals: (i) record French children speaking English in order to train an automatic speech recognition (ASR) software, and (ii) test the influence of robot-induced nudges in the children's performance while speaking in a foreign language. To that extent, we designed the following experiment. The participants are asked to complete a series of oral exercises in English: reading aloud, repeating and answering short questions. They rely on the content displayed on the screen of a computer and follow one of the experimenters' instructions (in French) and their replies are recorded on an ambient microphone. They are asked to repeat each exercise three times, and between each repetition, the Winky robot emits a reaction that is actually controlled by another experimenter in a Wizard-of-Oz setting. The nudges are designed so as to test the effect of both nudges and sludges on three axes: the participant's success or failure to complete the exercise in a satisfactory manner, the participant's attention or distraction, and finally the participant's well- or ill-being.

The reactions of the Winky were built beforehand by the research team by using the building blocks available in the Winky app. We created, for each axis, a "sludge" expression, a "nudge" expression and a reward expression, that are detailed below:

- Success / Failure
 - Sludge: the Winky is disappointed.
 - Nudge: the Winky is encouraging.
 - Reward: the Winky is in love.
- Attention / distraction
 - Sludge: the Winky seems bored or asleep.
 - Nudge: the Winky draws attention to the task.
 - Reward: the Winky is interested.
- Well-being / Ill-being
 - Sludge: the Winky is depressed.
 - Nudge: the Winky is reassuring.
 - Reward: the Winky displays complicity.

Once the data is collected, we hope to align it automatically using the open access alignment tool WebMAUS, the web interface of the Munich Automatic Segmentation System [50, 71]. We expect many alignment errors due mainly to two reasons: First, the speech is produced by children's voices, which may prove difficult to align with a tool trained on adult voices; Second, it will be accented speech, which means that the phones produced by the participant may be quite different from the canonical phones in the target language (English) and thus difficult to align for a system trained on typical native speech only. These errors will provide rich information on two levels. First, the error-rates should help

us categorize which productions were more successful, which in turn should help us measure the impact of the nudges and sludges. Second, they should help us design a more accurate ASR system, i.e., the first ASR system specifically designed to align child French-tainted English speech. This we hope will be implemented in future versions of the Winky robot so that it can automatically assess the success of the participant and react accordingly.

4 CONCLUSION

In this paper, we provide an overview of digital nudging strategies in education with a detailed account of their efficiency in knowledge acquisition by the learner and of their general, technical, and ethical limitations. We also present our methodologies for measuring the effects of nudging in learning for 2 ongoing projects (LeCycl and EduWinky).

All digital nudges using AI mechanisms as statistical inferences from users' behavior, are raising new ethical concerns [30]. In fact, these nudges augmented by AI reinforce the ability to achieve the designer goals using cognitive biases, emotional impulses and other human behavioural mechanisms both intentionally or unintentionally.

The article 5 of the proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (AI Act) states that putting into service or use an AI system that deploys subliminal techniques beyond a person's consciousness with the objective to or the effect of materially distorting a person's behavior shall be prohibited. Yet applying this rule to real cases is not straightforward. It is necessary to amplify the real-life tests with nudging systems in several application domains such as education to find how to mitigate the risks.

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