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La combinaison des approches énactive et vicariante lors de la formation des utilisateurs de systèmes d'information : une étude expérimentale

par

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Sommaire

La formation en analytique est une priorité pour les organisations qui sont de plus en plus nombreuses à recourir à des systèmes d'information permettant le traitement de données massives. En effet, les entreprises doivent s'assurer d'avoir de la main-d'œuvre qualifiée dans l'utilisation et l'interprétation de données. Il est donc pertinent de se questionner sur les moyens d'améliorer les méthodes de formation. L'apprentissage peut être divisé en deux approches différentes; l'apprentissage par la pratique (de manière énactive), et l'apprentissage par l'observation (de manière vicariante). Selon la littérature, une combinaison de ces deux approches permettrait d'augmenter les résultats d'apprentissages découlant d'une formation. Toutefois, il n'y a pas de lignes directrices sur la manière dont on intègre ces deux approches dans un curriculum. Par conséquent, l'objectif de cette étude est d'établir s'il y a un ordre optimal dans lequel ces deux types de formations devraient être intégrés afin de maximiser l'apprentissage. Pour ce faire, nous avons réalisé une expérience intra sujet auprès de 30 participants pour déterminer si l'ordre dans lequel on présente les formations a un impact sur les résultats d'apprentissage ainsi que sur l'efficacité de l'apprenant durant la tâche. Nos résultats suggèrent qu'il est préférable de débuter une formation par la portion vicariante afin d'augmenter l'efficacité des apprenants puisque les différences au niveau de l'apprentissage sont faibles.

Mots clés : Formation utilisateurs • ERPsim • Oculométrie • Tableaux de bord d'affaires • Visualisation de données

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Avant-propos

Ce mémoire présenté sous forme de deux articles complémentaires a été autorisé par la direction du programme de M.Sc. de HEC Montréal. Le consentement des coauteurs des articles a également été obtenu préalablement à la soumission de ce mémoire.

Le premier article a été soumis à la conférence Gmunden Retreat on NeuroIS 2016 tenue dans la ville de Gmunden en Autriche. Il a ensuite été publié par Springer dans Information Systems and Neuroscience: Gmunden Retreat on NeuroIS 2016 de la série *Lecture Notes in Information Systems and Organisation*.

Le deuxième article a été rédigé suite aux commentaires et à la rétroaction fournis par les participants à la conférence Gmunden Retreat on NeuroIS 2016. Il est actuellement en préparation pour le soumettre à la revue *Decision Sciences Journal of Innovative Education* (DSJIE).

Les articles ont été ajoutés au mémoire avec le consentement écrit des coauteurs.

Remerciements

Ce projet de mémoire a nécessité la contribution d'une multitude de gens incroyables et que j'aimerais remercier.

En premier lieu, j'aimerais remercier mes directeurs de maîtrise, Pierre-Majorique Léger ainsi que Patrick Charland qui m'ont accompagné durant cette longue épopée qu'a été ce projet de maîtrise. Vous avez su me laisser assez de liberté pour que je puisse m'épanouir dans la réalisation de ce projet tout en me guidant et en me donnant la confiance nécessaire. Je ne les remercierai jamais assez d'avoir cru en moi jusqu'à la dernière minute. Votre dévouement envers vos étudiants est une source d'inspiration.

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Je tiens également la direction du laboratoire ERPsim qui m'a permis de concilier la vie d'étudiants avec mon emploi ainsi que toute l'équipe du laboratoire qui m'a soutenu tout au long du processus.

Un merci spécial à Karl-David pour son soutien et ses conseils qui ont été inestimables au cours des derniers mois.

J'aimerais également remercier ma famille qui m'a encouragé à poursuivre mes études et qui m'a permis de me rendre où je suis.

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Chapitre 1 : Introduction

1.1 Mise en contexte

L'insuffisance des habiletés informatiques chez les employés et le manque de formation font partie des principales raisons qui font en sorte que les investissements et les projets d'implantation de systèmes d'information échouent ou bien n'apporte pas les gains, financiers ou opérationnels, escomptés (Dezdar & Ainin, 2011; Rajan & Baral, 2015; Somers & Nelson, 2001). C'est pourquoi la formation des utilisateurs finaux est identifiée comme étant un facteur clé de succès lors de l'implantation de système d'information (S. Gupta & Anson, 2014). Pour l'implantation de certains types de systèmes d'information tels que les progiciels de gestion intégrés (PGI) plus de 30% des coûts peuvent être imputés à la formation des utilisateurs (Scott & Walczak, 2009). Il devient donc important de se pencher sur les manières d'améliorer les formations aux utilisateurs afin de maximiser le retour sur investissement.

Aujourd'hui, la formation sur l'analyse de données devient une priorité pour les entreprises (Asamoah, Sharda, Hassan Zadeh, & Kalgotra, 2017). En effet, un rapport de la firme Gartner constate que l'analyse de données ainsi que les bases de données sont omniprésentes dans la plupart des industries tous secteurs confondus (Laney & Jain, 2017). La littérature observe que les organisations ont de plus en plus besoin d'employés qualifiés dans l'utilisation des technologies d'analyse de données (Watson, 2014). Ce besoin est si criant que certains chercheurs croient qu'il serait temps d'adapter les curricula traitant d'analyse de données pour les étudiants en administration (Asamoah et coll., 2017).

La littérature concernant la formation dans le domaine des systèmes d'information foisonne de recherches s'intéressant aux approches les plus efficaces pour former des utilisateurs. (Chiang, Goes, & Stohr, 2012; B. Gupta, Goul, & Dinter, 2015). La théorie sociale cognitive, telle que proposée par Bandura (A. Bandura, 1977; Albert Bandura, 1986, 2001), est l'une des plus souvent employées pour étudier l'apprentissage dans le domaine de l'éducation et des systèmes d'information. Cette théorie divise l'apprentissage en deux approches différentes; l'apprentissage par la pratique (de manière énactive), et l'apprentissage par l'observation (de manière vicariante).

1.2 Objectifs de l'étude et question de recherche

La littérature suggère qu'une combinaison de ces deux approches serait à privilégier afin d'augmenter l'efficacité d'une formation {Gupta, 2010 #7;Gupta, 2013 #8}. Toutefois, nous n'avons connaissance d'aucune étude qui a cherché à déterminer dans quel ordre ces deux types de formations devraient être intégrés dans un curriculum afin de maximiser les résultats d'apprentissage. Cette étude tentera donc de répondre à la question de recherche suivante :

Dans quel ordre devons-nous combiner les approches vicariante et énactive dans un contexte de formation afin de maximiser l'apprentissage et l'efficacité des apprenants?

1.3 Contributions potentielles

Cette étude tentera d'enrichir la littérature dans le domaine de la formation aux utilisateurs finaux en apportant des preuves empiriques de l'impact de l'ordre dans lequel on combine les différents types de formation sur l'efficacité de celle-ci. Cette étude pourrait également servir de référence lors du développement de plans de formation comportant des éléments de formation énactifs et vicariants.

Du côté de l'industrie, si les résultats sont concluants, cette recherche pourrait aider les professionnels de la formation aux usagers à mieux orienter le choix des méthodes de formation en ce qui a trait à l'utilisation des tableaux de bord et des systèmes d'information.

1.4 Information sur les articles

1.5.1 Article 1

Le premier article est un acte de conférence, qui a été soumis et accepté à la conférence scientifique *Gmunden Retreat on NeuroIS 2016* (Lafontaine, Léger, Labonté-LeMoyne, Charland, & Cronan, 2017). Cette conférence est chapeautée par l'organisation NeuroIS qui rassemble des chercheurs se spécialisant dans l'utilisation d'outils et de connaissances neuroscientifiques appliqués au domaine des technologies de l'information et de la communication.

1.5.1.1 Résumé de l'article 1

L'objectif de cet article est d'apporter un support empirique pour le développement de curricula intégrant à la fois des éléments de formation énactifs et vicariants. Plus spécifiquement, l'article s'intéresse à l'ordre dans lequel les deux éléments de formation sont présentés afin de déterminer s'il existe une séquence optimale afin de maximiser l'apprentissage. Ce premier article est principalement axé sur l'utilisation de l'oculométrie afin d'évaluer l'efficacité attentionnelle des apprenants lors d'une formation. Les résultats suggèrent que la séquence commençant par le traitement vicariant permet d'augmenter l'efficacité attentionnelle durant une tâche de formation énactive.

1.5.2 Article 2

Le second article est actuellement en préparation en vue d'être soumis au journal la revue *Decision Sciences Journal of Innovative Education* (DSJIE). Bien qu'il soit plus détaillé il reprend essentiellement les mêmes éléments que l'article précédent tout en y incorporant les commentaires et la rétroaction reçue lors de la présentation à la conférence *Gmunden Retreat on NeuroIS 2016*.

1.5.2.1 Résumé de l'article 2

Tout comme le premier article, l'objectif de cette étude est d'apporter un support empirique pour le développement de curricula intégrant à la fois des éléments de formation énactifs et vicariants. Plus spécifiquement, l'article s'intéresse à l'ordre dans lequel les deux éléments de formation sont présentés afin de déterminer s'il existe une séquence optimale afin de maximiser l'apprentissage et l'efficacité. Cet article s'intéresse autant à la dimension objective qu'à la dimension autoperçue de l'apprentissage et de l'efficacité. Nos résultats suggèrent qu'il est préférable de débuter une formation par la portion vicariante afin d'augmenter l'efficacité des apprenants puisque les différences au niveau de l'apprentissage sont faibles.

1.5 Contributions personnelles

Tableau 1. Contributions dans la rédaction des articles

Étape	Contribution et tâches effectuées
Définition des requis	Définition de la question de recherche et la problématique – 60 % ● L'équipe a contribué à la définition des questions de recherche et l'approche à adopter
Revue de la littérature	Effectuer la revue de littérature pour déterminer les éléments importants de la formation en système d'information et l'identification des construits pertinents – 100%
Stimuli	Création des tableaux de bord et des scripts de chargement de données pour l'utilisation d'ERPsim durant la collecte - 100% Création de la capsule de formation sur l'utilisation et la conception de tableaux de bord– 100%
Conception du design expérimental	Création des formulaires nécessaires pour la demande au CER – 100% Concevoir le protocole de l'expérience – 100% Création du matériel de formation pour l'expérience - 100% Préparation de la salle de collecte - 50% ● L'équipe du Tech3Lab s'est occupé de tous les éléments touchant les instruments de collecte.
Recrutement	Élaborer le formulaire de recrutement – 100%
Prétests et collecte	-Responsable des prétests - 100% -Responsable des collectes de données – 50% • À cause du grand nombre d'éléments techniques à contrôler durant la collecte de données, une assistante de recherche était également présente en tout temps.
Extraction et transformation des données	-Création des aires d'intérêts pour la préparation à l'extraction des données oculométriques. -Extraction et nettoyage des données oculométriques et des donnéesprovenant des questionnaires - 100%
Analyse des données	Analyses statistiques du mémoire – 80% ● Aide sur Stata et SPSS pour les analyses par le statisticien affilié au laboratoire.
Rédaction	Contribution dans l'écriture des articles – 100% ● Les coauteurs ont contribué tout au long de la rédaction en fournissant des commentaires et une rétroaction.

Chapitre 2 : Premier Article

Combining vicarious and enactive training in IS: Does order matter?

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Abstract: The objective of the article is to provide empirical support for curriculum development to instructors using enactive learning in IS. Specifically, we are interested in understanding which instructional design, combining enactive and vicarious learning, leads to the most effective learning achievement and development of self-efficacy. We compare the two different training sequences to determine which is the best combination of the two instructional designs (vicarious/enactive) to train people in using business dashboards efficiently. In a controlled lab environment, we collected (1) behavioural data (performance, software interactions) (2) oculometric data and (3) self-assessed self-efficacy data to assess the learning process and strategies. Our results show that providing the vicarious training first when using a combination of enactive and vicarious learning leads to a higher self-efficacy increase. It also has a significant impact on the attentional efficiency of students using dashboards in a business setting.

2.1 Introduction

End-user training is recognized to be a key factor in the success of information system implementations (Charland, Léger, Cronan, & Robert, 2016; Gupta & Anson, 2014). Training end-user for the business intelligence and analytics technologies will be especially important since Gartner predicts that by 2017, most business users will have access to technologies that will enable them to prepare and analyze data (Parenteau, 2014). Research suggests that enactive learning is a very effective way to engage new users with a system (Léger et al., 2012). Enactive learning implies that learning is a consequence of one's interaction with and feedback from the environment (Leger, Davis, Cronan, & Perret, 2014). However, research suggests that a combination of enactive learning and vicarious learning leads to greater learning outcomes compared to vicarious training alone (Gupta & Bostrom, 2013; Gupta, Bostrom, & Huber, 2010). Vicarious learning suggests that the trainees learn by reflecting on their observation of someone performing a targeted behaviour (Yi & Davis, 2003) which means that one can learn by observing the actions of another person and the associated consequences (Gupta et al., 2010).

If the best strategy is to combine enactive and vicarious training as suggested by research (Gupta & Bostrom, 2013; Gupta et al., 2010), it is important to determine the optimal order one should use these instructional designs in an IS training curriculum. Is it better to start with vicarious training activities followed by an enactive experience, or vice versa? We propose to answer this question by investigating the attentional efficiency of the participants. We conducted an eye-tracking study in which we controlled the order in which the participants received the vicarious and the enactive training.

2.2 Literature Review and Hypothesis

The eye movement research is based on the eye-mind assumption proposed by Just and Carpenter (Just & Carpenter, 1980), according to which the attention is closely linked to the direction of the gaze. This assumption is valid as long as the visual environment is relevant to the task at hand (Hyönä, 2010).

Eye-tracking techniques have been used in several studies to understand the interactions between cognitive processes and learning outcomes (Anderson, Love, & Tsai, 2014). One of the interesting features of the eye-tracking method is that it provides a way to track the encoding and attentional processes occurring during the learning phase (Hyönä, 2010).

In the literature, temporal eye-tracking measures have been found to be the most widely used in learning-related studies (Lai et al., 2013). Visit duration (i.e. cumulative duration of fixation within an area of interest) is considered as an indicator of the total amount of cognitive processing engaged with the fixated information (Ozcelik, Karakus, Kursun, & Cagiltay, 2009). Indeed, it has been suggested in the literature that learners give more attention and more time to complex problems than intermediate or easier problems (Hyönä, 2010; Lin & Lin, 2014).

Expertise has been shown in the literature to have an impact on eye movements during learning (Jarodzka, Scheiter, Gerjets, & van Gog, 2010; Mayer, 2010; van Gog, Paas, van Merriënboer, & Witte, 2005). Jarodzka suggests that experts tend to attend more relevant features of a complex dynamic stimulus than novices, and that their attention remains focused on relevant areas (Jarodzka et al., 2010). This difference between experts and novices may also be found between individuals with smaller differences in expertise (van Gog et al., 2005). Besides, practice over a period of time has also been found to make individuals fixate faster and proportionally more on task-relevant information (Haider & Frensch, 1996).

Prior knowledge is also a factor that has been identified in the literature as having a significant impact on measures of eye movements. A study from Canham and Hegarty suggests that newly acquired knowledge helped the learners focus their attention on task-relevant knowledge and less on task-irrelevant knowledge (Canham & Hegarty, 2010). Their study consisted of two experiments in which the participants made inferences from weather maps before and after they received instruction about relevant meteorological principles (Canham & Hegarty, 2010). Their results show that after receiving the instructions, the participants paid more attention to relevant information and less attention to irrelevant information (Canham & Hegarty, 2010). We thus pose the following hypothesis:

H — Vicarious training accelerates the attentional efficiency of the learner.

2.3 Method

Participants

To answer the research question, a between-subject experimental design with two conditions has been chosen. The conditions assigned to each subject determined the order in which they received the enactive and vicarious training.

During the experiment, each subject had to follow both a 15 minutes vicarious and a 15 minutes enactive training session. In the first condition, the participants were first given the vicarious training. The vicarious training consisted of a fifteen-minute demonstration video including a voiceover explaining the different principles that guided the creations of the different indicators and which of them were useful in the context of a given task. The participants then received the enactive part of the training in which they were asked to perform a task in the simulated business environment, i.e. ERPsim (Montréal, Canada) (Léger, 2006) using an online dashboard and an SAP GUI.

As illustrated in figure 1, the participants that were in the second condition followed the same protocol, but they received the enactive training first and then received the vicarious training. All the participants were asked to answer questionnaires assessing learning outcomes such as higher self-efficacy, objective knowledge, perceived difficulty of the training or satisfaction with the learning process (Gupta & Bostrom, 2013; Gupta, Bostrom, & Huber, 2010) before, between, and after the pieces of training.

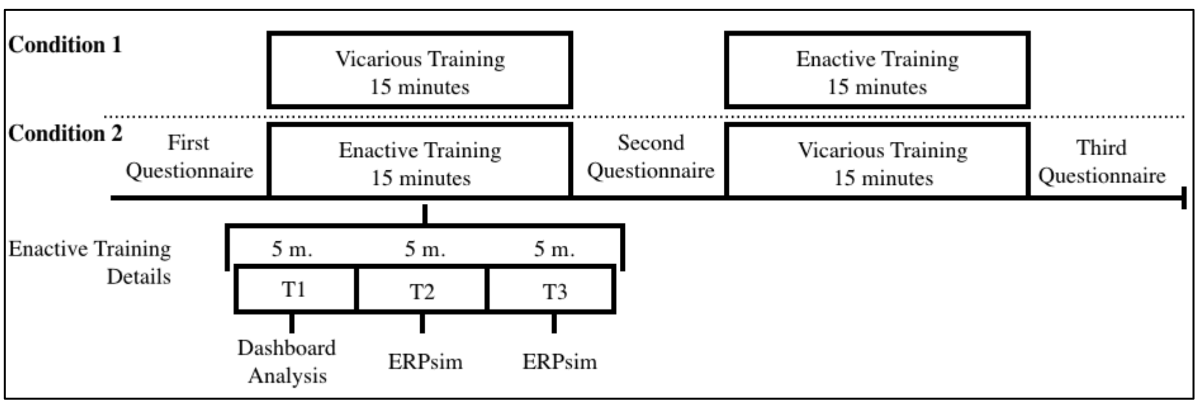

Fig. 1. Experiment timeline for both conditions

Design and Apparatus

The study was conducted using a platform to simulate a business environment called ERPsim (Léger, 2006). The ERPsim games are known for providing a realistic business context in which trainees are using a real ERP system (i.e. SAP (Walldorf, Germany)) to manage their organization (Léger, 2006; Léger et al., 2011; Léger et al., 2012; Leger et al., 2014). Specifically, the "Logistics" variant of the game, has been used for this experiment to provide the enactive learning context. The task involving ERPsim required the participants to make business decisions regarding the quantity of each of their 6 products that were to be sent in the three available regions.

To help them execute the task in ERPsim, the participants were provided a self-refreshing dashboard that displayed data for sales, inventory, and financial performance as well as a memory aid for the different rules of the game. The visual portion dashboards were designed using the design principles from Stephen Few's books *Show me the Numbers* (Few, 2012) and *Information Dashboard Design* (Few, 2013). The dashboard contained four types of indicators: useful information, well presented; useful information, poorly presented; useless information, well presented; useless information, poorly presented. In total, 4 versions of the dashboard were produced to randomize the disposition of the indicators in the screen.

Instrumentation

Attentional Efficiency: We define the attentional efficiency as the learner's ability to identify and process rapidly relevant information from the dashboards. The participant's attentional efficiency was assessed using the visual attention of the participant during the experiment. Visual attention is measured using eye-tracking devices (Tobii X60) monitoring participant's gaze. Visual attention provides an objective measure of what participants were considering in the dashboard to make decision (Riedl & Léger, 2016). Average visit duration was assessed for each type of indicator on the dashboard because it provides clear information on the time it takes the participants to process the information.

Learning Outcomes : Learning outcomes, and perceived difficulty of the training, were measured using questionnaires that were developed with the learning outcomes constructs from the literature (Gupta & Bostrom, 2013): a) participant's learning (objective knowledge) was measured by true or false questions with a certitude component, b) participant's perceived understanding of the dashboard design principles and c) the dashboard self-efficacy construct were measured using adapted elements from the self-efficacy items from Hollenbeck and Brief (Hollenbeck & Brief, 1987) to fit the experimental context of business dashboards, d) the participants' capacity to apply knowledge of dashboard usage was assessed with items oriented towards the main topics covered in Few (Few, 2012, 2013), e) the level of satisfaction with the learning process was measured using the scale from Green and Taber (Green & Taber, 1980), e) the perceived enterprise system management knowledge construct was measured using the items from Cronan and al. (Cronan, Léger, Robert, Babin, & Charland, 2012).

2.4 Results and Discussion

To assess the attentional efficiency used during the training, we analyzed the participants' eye-tracking data gathered during the enactive training. The vicarious training was excluded to avoid a bias linked to the explanations attracting attention to specific regions of the screen. The 15 minutes of the enactive training was divided in three 5 minutes' segments to be able to differentiate the ability of the participants at different points during the training. For the analysis, the indicators were regrouped into the four categories mentioned above and we regressed the average visit duration for each of the categories. One of the main purposes of a dashboard being to allow the user to quickly identify things that deserve attention and might require action (Few, 2013).

The results indicate that there are no significant differences between the two conditions for average visit duration on the indicators presenting useful information well presented. However, the condition 2 (enactive first) spent significantly more time on average every time they visited the indicators that presented either useless information or a poorly presented information or both of them (see table 1). For example, the participants that did not receive the vicarious training, stayed 0.5 seconds (coefficient value) longer ($p = 0.028^{**}$) than their counterparts every time they visited an indicator showing useful information poorly represented.

This is interesting because even though they had not received the vicarious training, the participants from condition 2 (enactive first) were still able to interpret the data from the good indicators as rapidly as those who had received the vicarious training. Also, after only 15 minutes of enactive training, participants from condition 2 (enactive first) managed to catch up those in condition 1 (vicarious first) by reducing the difference to insignificant levels in the average visit duration for the indicators showing useless information well presented. This shows that even though they start without prior knowledge of business dashboard principles, subject from condition 2 (enactive first) progressed quickly in the interpretation of the different types of indicators. We thus accept our hypothesis that vicarious training accelerates attentional efficiency, but we also observe that the effect seems to wear out as enactive learners are able to catch up rapidly. It is also interesting that the version of the dashboard did not have any significant impact on the attentional efficiency of the participants.

Table 1. Summary of attentional efficiency results: Regressions of the average visit duration (s) by condition for each type of indicators at the beginning (T1) and the end (T3) of the enactive training. The coefficient values represent the increase average visit duration for condition 2 (enactive first) participants.

Indicator Type	T1		T3	
	Coefficient (s)	P-value	Coefficient (s)	P-value
Useful information, well presented	-	-	-	-
Useful information, poorly presented	0.50	0.028**	0.48	0.003***
Useless information, well presented	0.23	0.078*	-	-
Useless information, poorly presented.	0.29	0.009***	0.24	0.046**

*= P<0.1; **= P<0.05; ***= P<0.01; ****= P<0,001

While the main objective of the paper was not to compare the learning outcomes, we observe that out of the learning outcomes measured, the order in which the participants received the training only had a significant impact on the dashboard self-efficacy and perceived enterprise system management knowledge. Precisely, the participants that started with the enactive training had a lower increase in self-efficacy (Coef. -.55, p-value = 0.079*), but had a higher increase in their perceived enterprise system management knowledge (Coef. .54, p-value = 0.079*). This means that there were no significant differences between the two groups for the increase in objective knowledge at the end of the experiment. This suggests that both groups progressed the same no matter the sequence in which the training were provided. There were also no significant differences between the two groups for the perceived difficulty of the training and the satisfaction with the training process at the end of the experiment.

2.5 Conclusion

Eye-tracking results indicate (visit duration) that the sequence in which vicarious and enactive training occurs has a significant impact on the visual search patterns of students. However, the participants that did not receive the vicarious training before the enactive one managed to interpret data from the good indicators as quickly as those who had received the vicarious training and the difference reduces quickly after less than 15 minutes of training.

Learning outcome results suggest that the order in which vicarious and enactive training are provided has no impact on objective knowledge acquisition, satisfaction and perceived difficulty of the training process, and on the trainee's perception of their own knowledge of dashboard concepts. However, participants who received the vicarious training first, had a higher increase in their dashboard self-efficacy, but had a lower increase in their understanding of enterprise system management knowledge than the participants that started with the enactive training. This implies that providing vicarious training first could lead to a higher academic performance in time compared to training methods where the enactive training is provided first because the correlation between self-efficacy and performance is stronger after a time lapse from the beginning of the learning experience (Honicke & Broadbent, 2016).

Thus, based on our results, instructors should begin with the vicarious training when using a combination of inactive and vicarious training to optimize objective knowledge acquisition and the feelings of self-efficacy. We prioritize the acquisition of self-efficacy because it has been suggested in the literature that it has an impact on future performance whereas such evidence has not yet been demonstrated for the enterprise system management knowledge construct.

Finally, we conclude that eye-tracking can be a useful tool for the study of learning process of IS users as it can detect how learners process certain material (van Gog et al., 2005). It could allow researchers to compare pedagogical scenarios and propose efficient training methods based on empirical data.

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Chapitre 3 : Deuxième Article

Combining vicarious and enactive training in IS : An Experimental Study

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Abstract: Training on analytics is now becoming a major preoccupation for organizations as the need for data literate professionals increases with more industries embracing the power of big data and data analytics. End-user training literature suggests that it might be more effective to combine enactive learning and vicarious learning to achieve better results. However, there is no guidelines on how to integrate those two approaches in a training curriculum. Therefore, the objective of this paper is to determine if there is an optimal sequence to combine enactive and vicarious training elements to achieve greater learning outcomes. To do so, we conducted an experimental study to assess the effect of the order in which vicarious and enactive elements are presented, on both the learning outcomes and the learners' task efficacy. These outcomes are also analyzed via both objective and self-perceived measures. Overall, our results indicate that the approach starting with the vicarious learning should be considered better when designing the sequence of a training curriculum since it increases the task efficacy of the learners without compromising their learning.

3.1 Introduction

Insufficient skills in the use of technologies by employees is one of the main reasons why investment in Information System technologies fail or fall short of the anticipated productivity gains (Dezdar & Ainin, 2011; Somers & Nelson, 2001; Rajan & Baral, 2015). This is why end-user training is one of the key success factors in information system implementation (S. Gupta & Anson, 2014). In the case of a major IS implementation such as Enterprise Resources Planning systems (ERP), more than 30% of the total project costs are attributable to end-user training (Scott & Walczak, 2009). Thus, improving the way we deliver technology-related training is a key element in ensuring continuous improvement in the productivity of organizations (Davis & Yi, 2004).

Nowadays, training on data analytics is becoming a major priority for organizations (Asamoah, Sharda, Hassan Zadeh, & Kalgotra, 2017). A report from Gartner suggests that data and analytics are becoming central to most of the industries, business functions, and IT disciplines (Laney & Jain, 2017). In the context of big data implementations, Watson (2014) states that besides the clear business needs, strong sponsorship, aligned business and analytics strategies, and a strong data infrastructure, the organization also needs people skilled in the use of analytics. According to Gartner, the current trend in most analytics and business intelligence (BI) program is to shift from providing prebuilt reports towards enabling self-service analytics for business users and providing them with more agile ways of consuming the data (Howson, Sallam, Tapadinhas, Richardson, & Idoine, 2017). The need for data literate professionals is so critical that we need to adapt and rethink analytics curriculums for business students (Asamoah et al., 2017).

There is a growing body of literature in IS education that focuses on finding the most effective ways to train users in IT and analytics (Chiang, Goes, & Stohr, 2012; B. Gupta, Goul, & Dinter, 2015). On the one hand, vicarious learning suggests that the trainees learn by reflecting on their observation of someone performing a targeted behavior, (Yi & Davis, 2003) which means that one can learn by observing the actions of another person and the associated consequences (S. Gupta, Bostrom, & Huber, 2010). On the other hand, a recent meta-analysis demonstrated that including elements of active learning in class is more efficient than the traditional lecture approach in the fields of Science Technology Engineering and Math (Freeman et al., 2014). This suggests that active learning should be considered as a serious option when designing new curriculums. Enactive learning has been the subject of several studies that suggest it is a very effective way of engaging new users with a system (Léger et al., 2012). The principal characteristic of enactive learning is that the learning is a consequence of one's interaction with the environment and the feedback he gets from it (Leger, Davis, Cronan, & Perret, 2014).

Some research suggests that it might be more optimal to combine enactive learning and vicarious learning to achieve better results (S. Gupta & Bostrom, 2013; S. Gupta et al., 2010). However, to our knowledge, no research has been conducted to determine the order in which those instructional designs should be embedded in an Information System training curriculum to increase the resulting learning. This brings us to the following question: Is it better to start with vicarious training activities followed by an enactive experience to maximize both participants' learning and task efficiency, or vice versa?

To answer this research question, we have conducted an experimental study where we controlled the order in which the participants received the vicarious and enactive pieces of training to assess the effectiveness of different instructional designs. We will first review the main concepts of the end-user training literature that have been used to frame this study, as well as prior experiment focusing on enactive and vicarious learning. We will then detail the methodology, the experimental stimuli, the measures used and their instrumentation. The results will then be presented and interpreted in the lights of the literature presented earlier. Finally, we will conclude this paper with the potential contribution for researchers and practitioners as well as insights for future research in this field.

3.2 Literature Review and Hypothesis Development

The Social Cognitive Theory (SCT) as proposed by Bandura (1977; 2001; 1986) has been one of the most widespread theories used to comprehend participants' learning in the fields of Education and IS (S. Gupta et al., 2010). This theory suggests that a reciprocal relationship between an individual, his behaviour as well as the environment can be illustrated as one's belief in his ability to learn or perform a behaviour (self-efficacy) (Bandura, 1986; Schunk, 2012). This also suggests that learning not only comes from the interaction with the environment but can also come from observing the behaviour of others (Bandura, 2001; Schunk, 2012). This theory brings two different approaches to learning, one that is focused on "doing" (enactively) and another that is more reliant on "observing" (vicariously).

Vicarious learning which is also known as behavioural modelling focuses on the importance of observing behaviours and reactions of others in order to learn (Bandura, 1977; Bandura, 2001; Schunk, 2012). This can be as simple as watching someone do a specific task and then try to replicate it (Yi & Davis, 2003). In the literature, vicarious learning often takes the form of a video containing a demonstration made by an instructor (S. Gupta et al., 2010). This is the approach that is the most common in end-user training literature and it has been shown as providing better learning outcomes than more conventional methods such as lectures or readings from a manual (S. Gupta et al., 2010). Some research also suggests that vicarious methods are yielding better results than regular training methods when the complexity of the task increases (Bolt, Killough, & Koh, 2001).

Enactive learning theory suggests that learning occurs by observing the consequences of our own actions (Bandura, 1977). We then retain the behaviours that resulted in successful consequences and we tend to modify or abandon those that led to negative outcomes (Bandura, 1977). Serious educational games and simulations are prime examples of the incorporation of enactive learning in a training context as they usually provide feedback in response to learner actions. Literature suggests that serious games and other similar technologies can lead to increased learning outcomes, notably self-efficacy and both procedural and declarative knowledge (Sitzmann, 2011).

Some research suggests that a combination of both vicarious and enactive elements leads to better results than vicarious alone (Bandura, 1986; S. Gupta & Bostrom, 2013; S. Gupta et al., 2010). The most common method that combines both types of training is what you would expect in a classic class setup; you show the learners how to accomplish a task and then you put them in a situation where they have to execute the same task. This is the approach that has been selected for the combination of vicarious and enactive learning methods in the study from Gupta & Bostrom (2013). The tool they used for their experiment has been developed according to best practices from both the industry and instructional design principles (S. Gupta & Bostrom, 2013). Another example of a training curriculum that combines enactive and vicarious learning is the ERPsim simulation in which the recommended course of action is to start by the vicarious part (Leger et al., 2014).

Gupta suggested that "[t]he goal of an end-user training program is to produce a motivated user who has the skills needed to apply what has been learned to perform a job-related task" (S. Gupta et al., 2010:10). From this definition, we can identify two key components of successful training; getting the knowledge on how to do a task, developing the skills to execute it.

Building upon the aforementioned studies from Gupta & Bostrom (2013) and Léger (2014) that used a starting with the vicarious training, it would lead us to believe that this classic sequence is optimal.

We thus pose the following hypothesis:

H1 — Providing participants with the vicarious training first will provide greater learning outcomes.

In his literature review, Gupta (2013) defines learning outcomes as being the degree to which the learners have been trained in the system in terms of knowledge, self-efficacy, and satisfaction with the learning process. Those learning outcomes can be divided further into two distinct categories: objective measures, and self-perceived measures.

This distinction between the learning outcomes allow us to further divide our hypothesis into two sub-hypotheses:

H1A — Providing participants with the vicarious training first will provide greater objective learning outcomes.

H1B — Providing participants with the vicarious training first will provide greater self-perceived learning outcomes.

However, knowledge alone is not sufficient enough to evaluate the quality of end-user training, we must also know if the learner is competent in the training task at hand (Charland et al., 2016). While we are mostly interested in the effect at the end of the training, we still believe that we need to evaluate the participants' ability to perform during the training task. We propose to measure this competency via the participants' task efficacy. Once again, the task efficacy can be measured with both objective and self-perceived measures.

Objective Task Efficacy

Eye-tracking methods provide a way to track the attentional processes of the learners during the learning phase (Hyönä, 2010). They have also been used in a large number of studies to understand the interactions between the cognitive process and the learning outcomes (Lai et al., 2013).

Research in eye tracking suggests that expertise, practice, and prior knowledge have an impact on the visual attention of the participants during learning tasks (Jarodzka, Scheiter, Gerjets, & van Gog, 2010; Mayer, 2010; van Gog & Scheiter, 2010). This suggests that the visual attention of the participants can be used as a proxy of this efficacy.

Another study also showed that recently acquired knowledge can also have an impact on visual attention during the task (Canham & Hegarty, 2010). This study had participants who had to make inferences from weather maps before and after receiving instructions regarding relevant meteorological principles. Their results suggest that after receiving the instructions, the participants focused their attention more on task-relevant information and less on irrelevant information. Seeing how the vicarious training segment is similar to receiving instructions, we posit the following hypothesis:

H2A — Providing participants with the vicarious training first will lead to a greater objective task efficacy.

Self-Perceived Task Efficacy

Self-efficacy is defined in the literature as being one's perception of his own ability to perform actions (Schunk, 2012). Prior research on self-efficacy suggests that self-efficacy is mainly domain-specific, inviting us to adapt it to the task or goal at hand (Pajares, 1996; Schunk, 2012). In the literature, self-efficacy has been identified as being strongly correlated with performance (Honicke & Broadbent, 2016). The results from a recent study that explored the relationship between self-efficacy and performance suggest that there is a reciprocal effect between them over time. This further highlights the importance of self-efficacy in the context of end-user training (Talsma et al., 2018).

This relation, between performance and self-efficacy, allows us to develop a further hypothesis. If participants that have received the vicarious training prior to the enactive activity are indeed more efficient at doing a task, we could suppose that they also have a higher self-perceived task efficacy. We thus pose the following hypothesis:

H2B — Providing participants with the vicarious training first will lead to a greater increase in self-perceived task efficacy.

3.3 Methodology

To test our hypothesis, a laboratory experiment was conducted using a between-subjects experimental design with a sample size of 30 participants (Male=12, Female=18). This study was based on psychometric and performance data gathered through questionnaires as well as oculometric data from an eye-tracking device. The study, as well as the experimental protocol, have been reviewed and approved by our institution's Ethical Review Board and all the participants had to give their informed consent to take part in the study. The participants were recruited through a university panel that is comprised of university-level students. Each experiment lasted 2 hours and the participants were given a compensation of 30$.

3.3.1 Experimental design

The experiment had two conditions determining the order in which the subjects received the training parts, that were randomly assigned to them (*Vicarious first* - Condition 1 =15, *Enactive first* - Condition 2 =15). Based on the research question, the two conditions comprised the same two elements of training (i.e. vicarious and enactive elements) but differed from each other in the order in which they were presented.

In condition 1, the 30-minute training segment of the experiment was composed of a 15 minutes vicarious training as well as a 15 minutes enactive training. All the participants were asked to answer questionnaires assessing both perceived and objective learning outcomes before and after the training.

As illustrated in Figure 1, the participants that were in Condition 2 followed the same protocol, but they were presented with the enactive training first followed by the vicarious one.

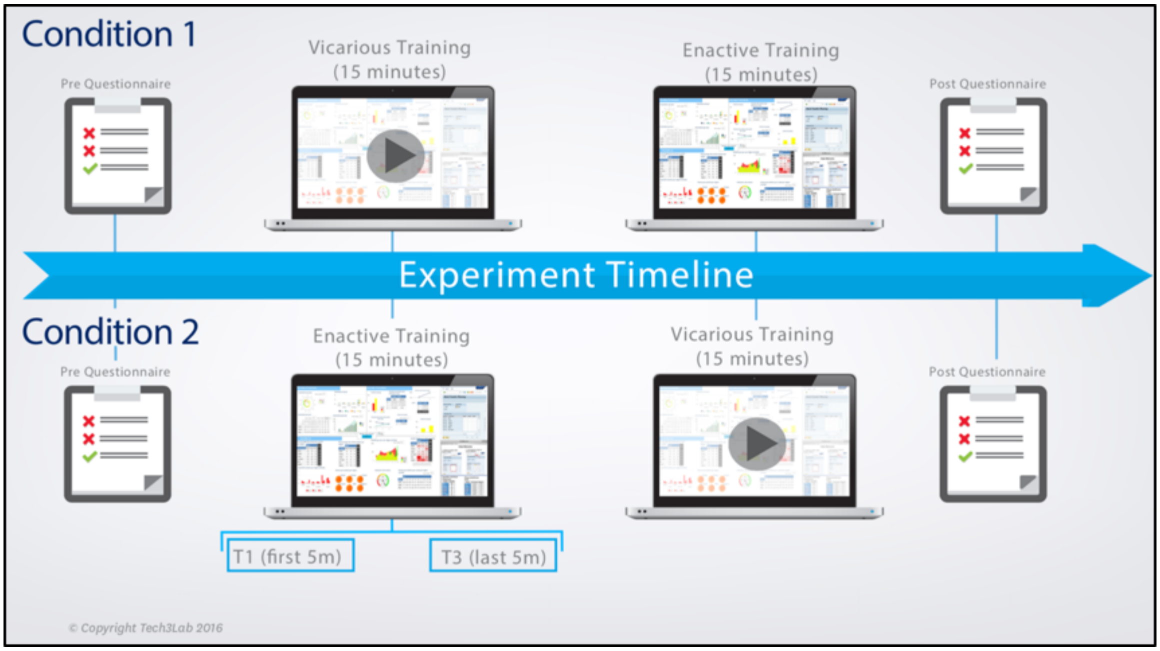

Fig. 1. Experiment timeline for both conditions

3.3.2 Experimental stimuli

ERPsim was used as the experimental research platform for this experiment. ERPsim is a business simulation that provides a realistic context in which learners are using a real ERP system (i.e. SAP (Walldorf, Germany)) to manage their virtual organization (Léger, 2006).

This technology has been used in more than 377 universities worldwide by more than 832 professors, lecturers and professional trainers in various fields to provide a way of increasing the engagement of their students during their courses (Charland et al., 2016). ERPsim has been used in experimental studies in various fields ranging from neuroIS to ERP learning research (Charland et al., 2016; Cronan et al., 2012; Léger, 2006; Léger et al., 2011; Léger et al., 2012; Leger et al., 2014).

From the numerous pedagogical objectives being supported by this simulation, we retained two of them which were to be used during the experiment. The first one was the understanding of the concepts of integrated business processes in organizations using ERP software. The second one was the use of analytics tools to delve into the data to get insights on enterprise performance. Based on these requirements, we decided to use the Logistics variant of the simulation in order to minimize the complexity of the scope as it is a simpler version of the game that is often used in the introduction to management information system (MIS) courses.

An extension to the ERPsim Game, ERPsim-BI was also used to enable the analytics portion of the game. ERPsim-BI consists of an external SQL database in which selected transactional data from the SAP system is transferred to allow external software to reach the data via SQL queries. This was of tremendous importance, as when the data was collected, there were no other tools available that could provide a real-time analytics component to the ERPsim simulations games. This technology is what allowed us to provide participants with a self-refreshing online dashboard that displayed data such as sales, inventory and financial performance from their fictitious organization.

The visual portion dashboards were designed using the design principles from Stephen Few's books *Show me the Numbers* (Few, 2012) and *Information Dashboard Design* (Few, 2013). Figure 2 presents an example of the four types of indicators contained in the Dashboard:

1. Useful information, well presented
2. Useful information, poorly presented
3. Useless information, well presented
4. Useless information, poorly presented

In total, 4 versions of the dashboard were produced to minimize the impact of the disposition of the indicators on the screen. For example, Figure 2 shows the inventory section of the dashboard. In this case, the top left corner is useless information (Daily Inventory) as it doesn't allow participants to differentiate products inventory and is poorly presented since radar charts have been shown as being harder to comprehend than tables and bar charts (Few, 2013). On the other hand, the top right indicator (Actual Inventory) is the useful information, well presented, as it provides an easy way to know the current levels of the stock for each product in every region. This was the most relevant inventory information available to make the stock transfer decision that was central to the task.

Fig. 2. An example of the four inventory indicators in the dashboard: 1. Useful information, well presented; 2. Useful information, poorly presented; 3. Useless information, well presented; 4. Useless information, poorly presented.

3.3.3 experimental protocol

Enactive Training

The enactive part of the training consisted of a 15-minute simulation of a logistics task in the ERPsim simulation game. During this training, the participants were asked to fulfill the role of a stock distribution manager in a company that sold dairy products. Since the simulation is normally played in teams, we specifically designed our experiment around a specific role in the company that is responsible for managing the inventory levels and dispatch the products from the main warehouse to different regions: North, South, and West. The only task the participants were asked to perform in the SAP GUI was the stock transfer transaction. This transaction requires the participants to determine the quantity of each of the 6 products to be sent in the three available regions.

To execute the task, the participants must analyze the data provided from the first round of the game using the aforementioned business dashboard. They had 5 minutes to analyze the provided dashboard, followed by 10 minutes of simulation during which 10 virtual days would come to pass (1 minute per virtual day). The impact of the decisions taken by the participants would be visible on the business dashboard every minute after the automatic update of the data, providing them with feedback on their decisions in the form of updated data visualizations.

Vicarious Training

The vicarious training consisted of a 15-minute demonstration video including a voiceover. The first 5 minutes were spent explaining the different principles that guided the creation of the business dashboard indicators such as the usefulness of the indicators as well as the quality of the presentation. The following 10 minutes were devoted to the simulation during which participants could see decisions taken by the trainer as well as hearing the rationale behind those decisions. For example, they were shown which of the indicators were useful and how to interpret those in the context of the given task which was to take a stock transfer decision in order to maximize the profit of the virtual company. Figure 3 shows a screenshot from the vicarious training video on which we can see a transparent blue square highlighting the indicator being explained.

Fig. 3. Screenshot from the vicarious training video during the explanation of the highlighted indicator (transparent blue square).

3.3.4 Operationalization of the research variables

The learning outcomes were operationalized via objective measures and self-perceived measures as presented in Table 1 below. The objective measures were developed with the learning outcomes constructs used by Gupta (2013) in his paper comparing different training methods. The objective knowledge and the certitude were assessed via true or false questions with a certitude component. The objective knowledge is measured as a percentage of good answers and the certitude is a percentage the number of questions for which the participants were certain of their answer. The self-perceived learning outcomes were measured via multi-items 7 points Likert scales. The perceived ES management knowledge represents the self-perceived understanding of the impact and the use of an ERP in an organization and how it affects it. This construct has been developed and used in prior research related to learning in an enactive context using an ERP as the stimuli (Cronan et al., 2012). The perceived dashboard knowledge represents their perceived understanding of the dashboard design principles and has been adapted from the self-efficacy items from Hollenbeck and Brief (1987) to fit the context of business dashboard best practices.

The objective task efficacy was assessed via the visual attention of the learner. The visual attention was measured using an eye-tracking device (Tobii X60, Danderyd, Sweden) that monitored the gaze of the participants throughout the experiment. The vicarious training segment was excluded from the eye-tracking analysis to avoid a bias caused by the explanations attracting attention to specific regions of the screen. We analyzed specifically the last 5-minute segment of the enactive training to be able to compare the efficacy of the participants toward the end of the “hands-on” portion of the training. To do so, we used the average visit duration which has been suggested as being a good indicator of the total cognitive processing engaged with the fixated information (Ozcelik, Karakus, Kursun, & Cagiltay, 2009). In our context, we consider that a lower visit duration time is better because of the nature of the dashboards that are built to provide a quick interpretation of the indicators (Few, 2013). We also measured the total visit count on the different types of indicators. This measure will provide data to understand what indicators the participants are gazing on more often. The more efficient the learner will be, the less he should visit poor indicators or irrelevant data.

The self-perceived task efficacy has been measured using a dashboard self-efficacy construct adapted from the self-efficacy items from Hollenbeck and Brief (1987). It has been adapted to assess the perceived ability of the participants to use business dashboards.

Table 1. Operationalization of the research variables

	Learning	Task Efficacy
Objective Measures	• Objective knowledge • Objective knowledge certitude	• Visual Attention
Self-Perceived Measures	• Perceived (ES knowledge) • Perceived Dashboard Knowledge	• Dashboard self-efficacy

Data analysis

To test our hypothesis, we developed a linear regression model to assess the impact of the order in which the vicarious and enactive learning is given on the different learning outcomes and task efficacy. We also controlled the following extraneous variables with; the condition, the version and the orientation of the dashboard, the synchronization problems with the dashboard, and prior experience with ERPsim. The models were then refined by removing extraneous variables that had no significant impacts. The statistical analysis was done using Stata/MP 15.1 and SPSS.

3.4 Results

Learning Outcomes

Our first hypothesis (H1) suggests that the participants that are presented with the vicarious training first will achieve higher learning in both objective (H1A) and self-perceived (H1B) measures.

For the objective learning portion of the hypothesis, we compared the effect of the condition variable (i.e. the order in which the participants received the pieces of training) on both the ratio of good answers in the objective knowledge questions (obj_kno) as well as their certitude regarding their own answers (obj_kno_cert). We have found no significant relationship between the condition and the increase in either objective knowledge measures in Table 2. The absence of significative difference in objective learning measures means that Hypothesis H1A is rejected.

Table 2. Results of linear regressions for questionnaire data

Variable		**DSE** reg1d	**ES** reg2b	**Perc_Kno** reg5b	**Obj_Kno** reg6b	**Obj_Kno_Cert** reg7b
Condition[1]	Coeff.	-0,5467**	0,5417**	-0,6121**	-0,0525	-0,0336
	(s.e.)	(0,3001)	(0,2964)	(0,2994)	(0,0461)	(0,0774)
Dashboard[2]						
1				-0,6353	0,1028	
				(0,4573)	(0,0771)	
2				0,1274	-0,14811**	
				(0,4497)	(0,0697)	
3				-0,3849	0,0910	
				(0,4220)	(0,0656)	
Orientation[2]					-0,1149**	
					(0,0529)	
ERPsim_Exp[2]			-0,6552**	-0,5975	0,0151	-0,0492
			0,0369	0,0887	0,7729	0,5321
_cons		0,4933**	0,5641*	1,5956***	0,2314***	0,3284****
		(0,2122)	(0,2840)	(0,4697)	(0,0739)	(0,0742)
N		30	29	29	29	29
F		3,3193	4,9581	1,4243	2,9785	0,2540
r2		0,1060	0,2761	0,2364	0,4482	0,0192
r2_a		0,0741	0,2204	0,0704	0,2977	-0,0563
p		0,0792	0,0150	0,2529	0,0277	0,7776

1. Unilateral test level of significance
2. Bilateral test level of significance

** p<=0.050
*** p<=0.010
**** p<=0.001

For the self-perceived part of the first hypothesis (H1B), we once again compared the effect of the condition on the self-perceived ES management knowledge (ES) and self-perceived knowledge of the dashboard design rules and principles (Perc_kno). While there is no significant difference for the self-perceived dashboard principles knowledge between the two conditions, results from Table 2 suggest that receiving the enactive training first will lead to a greater increase in the ES management knowledge of the participants (coeff. = 0.5417, p<=0.0396). This suggests that receiving the vicarious training first would provide a lower increase in self-perceived knowledge, thus causing Hypothesis H1B to be rejected.

Task Efficacy

Table 3 presents a summary of the impact of starting the enactive training first (condition variable dummy = 1) on the eye-tracking measures used to assess the objective task efficacy of the participants. The complete regression tables for both visit duration and visit count can be found in the Appendix. While there are no significant differences in the average visit duration for the indicators that were well presented, we can see that participants that began with the enactive training spent on average more time each time they visited an indicator that was poorly presented. This difference is significative for poorly presented indicators whether they present useful information (coeff. = 0.4776, p<=0.0026) or useless information (coeff. = 0.2384, p<=0.0456).

The difference in visual attention for participants from the two conditions is further highlighted when we look at the average visit count per indicator type. There are significant differences in the average visit count for the indicators that are either poorly presented or contains irrelevant information for the task at hand. Participants that did not receive vicarious training prior to the enactive task (condition dummy variable = 1) visited more frequently the wrong indicators than participants in the other condition. This stands true for indicators presenting: useful information poorly presented (coeff. = 15.6366, p<=0.0278), well presented useless information (coeff. = 20.0817, p<=0.0021), and useless information poorly presented (coeff. = 12.6606, p<=0.0323).

These results for the visual attention measures seem to indicate that participants that started with the vicarious training were more efficient during the learning task as they were able to process information more rapidly (visit duration) and visited less often the wrong indicators (visit count). We can thus affirm that the hypothesis H2A is supported by those results.

Our last hypothesis (H2B) states that participants starting with the vicarious training will achieve a higher increase in self-perceived task efficacy. The results from Table 2 showing that starting with the enactive training (condition dummy variable = 1) will significantly reduce the increase of dashboard self-efficacy (DSE) (coeff. = -0.5467, p<=0.0396) allow us to confirm that this hypothesis is supported.

Table 3. Impact of enactive training first on attentional efficiency per indicator type

	Average Visit Duration	Average Visit Count
Indicator Type	Coefficient in seconds Standard deviation p-value	Coefficient in number of visits Standard deviation p-value
Useful information, well presented	-0.3555 (0.2463) 0.1652	-6.0200 (8.4237) 0.4835
Useful information, poorly presented	**0.4776***** (0.1375) 0.0026	**15.6366**** (6.5651) 0.0278
Useless information, well presented	0,2256 (0.1671) 0.1930	**20,0817***** (5.6487) 0.0021
Useless information poorly presented.	**0.2384**** (0.1114) 0.0456	**12.6605**** (5.4816) 0.0323

*= P<0.1; **= P<0.05; ***= P<0.01; ****= P<0,001

Table 4. Summary of hypotheses

Hypothesis	Description	Conclusion
H1A	Providing participants with the vicarious training first will provide greater objective learning outcomes.	Not supported
H1B	Providing participants with the vicarious training first will provide greater self-perceived learning outcomes.	Not supported
H2A	Providing participants with the vicarious training first will provide greater objective task efficacy.	Supported
H2B	Providing participants with the vicarious training first will provide a greater increase in self-perceived task efficacy	Supported

3.5 Discussion

Our results suggest that the order in which the participants received their training has no impact on the increase of both the ratio of good answers in the objective knowledge questions and their certitude towards their answers. Individuals from both conditions progressed the same from the pre-questionnaire to the post-questionnaire. This suggests that contrary to our hypothesis, providing the pieces of training in any order will have no impact on the objective learning outcomes. Moreover, it is important to note that this was measured via true or false questions with a certitude component as well as with multiple-choice questions. It would be pertinent for future research to compare the performance in a graded exam context with essay questions.

However, even though there are no significant differences in the objective knowledge measures, the order of the training seems to have an impact on the increase of perceived enterprise system (ES) management knowledge. Indeed the participants that started with the enactive training first had a greater increase in their self-perceived understanding of the impact and the use of an ERP in an organization and how it affects it. Another finding regarding this variable is that participants who had prior experience with ERPsim (i.e. in a class setting) had a weaker increase in their self-perceived ES management knowledge. This could suggest that those students were already seeing themselves as being more knowledgeable about enterprise systems since they had at least one course related to management and information systems.

As for the participants' self-perceived knowledge of dashboard design principles (Perc_Know), even though the model is not significant, the condition seems to have a significant impact on that variable. Replicating the experiment with a greater sample size would allow us to assess whether the model becomes significant or not.

For the objective evaluation of the participants' task efficacy, our findings provide evidence that receiving the vicarious training prior to the enactive training has an impact on the visual attention of the participants during the task. The participants that had received the vicarious training were less likely to gaze at the wrong indicators and spent less time on average every time they looked at one of those. This means that participants that started with the enactive training were more likely to have their gaze drawn towards suboptimal indicators for their task, and thus were more inefficient. Moreover, they spent on average more time on the flawed indicator suggesting that they were unable to process the information as rapidly as the participants that had the vicarious training before. This seems to be consistent with previous studies in which participants with prior knowledge and/or expertise were focusing their attention on more task-relevant information (Canham & Hegarty, 2010; Haider & Frensch, 1996; Jarodzka et al., 2010).

However, other results suggest that there is no difference between the two conditions for both the visit duration and visit count for the indicators that were well presented and relevant to the task. This suggests that the participants from Condition 2 (enactive first) were able to interpret the good indicators as quickly as the participants from Condition 1 (vicarious first). This result is interesting because it implies that at the end of the enactive training, all the participants had similar visual attention on the task-relevant information while it was significantly different on the other indicators whether they already had the vicarious training or not. This suggests that while the vicarious training does not seem to increase the target behaviour (using good indicators), it significantly reduces the time spent on information.

While it is important to objectively evaluate the task efficacy, the self-perceived measures can add some useful insights and give us a broader view of the situation. Indeed, the results from H2B suggest that receiving the vicarious before the enactive training will lead to a higher increase in the participant's dashboard self-efficacy. This is intriguing knowing that self-efficacy constructs have been identified in the literature as being correlated with higher academic performance (Honicke & Broadbent, 2016). While we don't see any difference in the objective measures of learning, this might be due to the fact that the correlation between self-efficacy and performance is usually stronger after a certain amount of time after the learning experience (Honicke & Broadbent, 2016).

That being said, it would be important to investigate further to make sure that this difference in dashboard self-efficacy is not being an example of the Dunning Krueger effect (Kruger & Dunning, 1999). That theory states that incompetent individuals are more likely than their competent peers to overestimate their competency and performance towards specific objectives (Kruger & Dunning, 1999). In our case, were the participants under the impression that they were proficient at using dashboard because the scope and the duration of the training were quite narrow, or were they really as good as they thought? Future research could evaluate the long-term effect of the training to assess the real competency and performance of the participants in a given field to make sure that the self-efficacy reflects their actual level of proficiency.

While our findings cannot be generalized to a broader spectrum of training, it provides new insights into the impact of the order of training activities in a curriculum and opens new research avenues.

3.6 Conclusion

The objective of this paper was to determine if there is an optimal sequence to combine enactive and vicarious training elements to increase the resulting learning. To do so, we have been investigating the effect of the order in which we combine vicarious and enactive elements on both the learning and the efficacy outcomes. These outcomes were also analyzed via objective measures as well as self-perceived one. Overall, our results indicate that there are significant differences between the two approaches that should be taken into account when designing the sequence of a training curriculum.

From an objective standpoint, there is no difference in the knowledge increase of the participants whether they had the vicarious training first or not (H1A). However, contrasting with our H1B hypothesis, receiving the vicarious training first lead to a lower increase for one of the two self-perceived learning measures. The self-perceived ES management knowledge seems to increase more if you start the training with the enactive elements.

There are also significant differences regarding the task efficacy between the participants that started with the vicarious training and those that started with the enactive training. Those differences are present for the objective measure as well as the self-perceived ones. Indeed, eye-tracking data suggests that participants from Condition 1 (vicarious first) were more competent in the use of the different dashboard indicators (H2A). Moreover, they also had a higher increase in their dashboard self-efficacy (H2B).

These finding taken together would lead us to recommend providing the vicarious elements of the training before the enactive elements in a context where you want to combine both. While this recommendation does not maximize the increase of the self-perceived ES management knowledge, it grants the participants a greater increase in dashboard self-efficacy and ensures that they are more efficient during the enactive learning task. We prioritize the self-efficacy construct when developing curriculum given the corpus of literature that correlates self-efficacy with performance and academic success (Honicke & Broadbent, 2016) whereas there is no such evidence for the enterprise system knowledge management construct.

This paper provides an initial attempt at evaluating the impact of the sequence of training elements on the learning outcomes and task efficacy. However, as with any research, this study is not exempt of limitations. First, the sample was limited to university students which prevent the findings from being generalizable to other types of end-users such as employees in organizations. Second, the duration of the training is another limit that reduces the reach of this study. The total length of the two training elements combined was 30 minutes only, which is way shorter than the usual class taught at university. Moreover, since there was no follow up to the experiment, it is impossible to predict the long-term effect of the training on the participants. It would then be interesting for future research to do a longitudinal study to assess the impact of the sequencing of vicarious and enactive training elements for longer training sessions as well as the effects over time on knowledge retention and competencies.

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Appendix

A. Regression results for the average visit duration per indicator type

		VD_BB Mean_T3		VD_BM Mean_T3		VD_MB Mean_T3		VD_MM Mean_T3	
Variable		**reg16b**		**reg17b**		**reg19b**		**reg20b**	
Condition	**Coeff.**	-0,3555		0,4776	***	0,2256		0,2384	**
	(s.e.)	(0,2463)		(0,1375)		(0,1671)		(0,1114)	
	p-value	0,1652		0,0026		0,1930		0,0456	
Tableau_de_bord									
1		0,0619		-0,0601		0,0583		-0,1407	
		(0,2546)		(0,2534)		(0,2272)		(0,1256)	
		0,8105		0,8152		0,8002		0,2766	
2		0,0918		0,3187		0,0935		0,1018	
		(0,2722)		(0,2431)		(0,1544)		(0,0967)	
		0,7397		0,2056		0,5521		0,3059	
3		-0,2595		0,0820		0,1963		-0,1360	
		(0,2522)		(0,1766)		(0,1821)		(0,0975)	
		0,3165		0,6478		0,2947		0,1791	
Orientation		0,1075		0,2584	*	-0,1145		0,1265	
		(0,2151)		(0,1457)		(0,1418)		(0,0888)	
		0,6229		0,0923		0,4293		0,1705	
Synchro		0,2105		-0,0785		-0,2578		0,0090	
		(0,2817)		(0,1451)		(0,1657)		(0,1149)	
		0,4640		0,5948		0,1362		0,9387	
V2_Inst		-0,3879		0,4968	**	0,2025		-0,1123	
		(0,2491)		(0,1811)		(0,2203)		(0,1124)	
		0,1359		0,0129		0,3696		0,3302	
ERPsim_Exp		-0,1700		0,0602		-0,4116	**	0,0335	
		(0,1805)		(0,1595)		(0,1848)		(0,0855)	
		0,3583		0,7099		0,0382		0,6995	
_cons		1,6381	****	-0,1451		0,7565	***	0,4834	****
		(0,3993)		(0,2900)		(0,2324)		(0,1208)	
		0,0006		0,6226		0,0042		0,0008	
N		28		28		28		28	
F		1,0719		3,0747		4,0875		3,6881	
r2		0,2297		0,5485		0,4388		0,4731	
r2_a		-0,0947		0,3584		0,2026		0,2512	
p		0,4221		0,0212		0,0056		0,0093	

*= P<0.1; **= P<0.05; ***= P<0.01; ****= P<0,001

Where BB = useful indicators, well presented; BM = useful indicators, poorly presented; MB = useless indicators, well presented; MM = useless indicators, poorly presented.

B. Regression results for the visit count per indicator type

Variable		VC_BB_T3 reg23b		VC_BM_T3 reg24b		VC_MB_T3 reg26b		VC_MM_T3 reg27b	
Condition	**Coeff.**	-6,0200		15,6366	**	20,0817	***	12,6605	**
	(s.e.)	(8,4237)		(6,5651)		(5,6487)		(5,4816)	
	p-value	0,4835		0,0278		0,0021		0,0323	
Tableau_de_bord									
1		-9,4874		-0,8394		-6,6978		-0,7730	
		(9,9114)		(12,5832)		(7,8631)		(8,6349)	
		0,3505		0,9475		0,4049		0,9296	
2		-17,8000		4,6220		11,9874	*	11,6437	
		(11,4946)		(7,4345)		(6,6711)		(9,2613)	
		0,1381		0,5415		0,0883		0,2239	
3		-2,3601		3,1092		7,4859		-6,8086	
		(11,1339)		(10,3488)		(7,0045)		(7,6339)	
		0,8344		0,7671		0,2986		0,3836	
Orientation		-1,7496		-3,7344		0,9147		-2,9067	
		(8,9936)		(9,0329)		(7,3556)		(6,9512)	
		0,8478		0,6839		0,9023		0,6805	
Synchro		-0,5028		-2,2261		-5,2024		3,3510	
		(8,8268)		(8,8331)		(5,4714)		(5,9186)	
		0,9552		0,8037		0,3536		0,5779	
V2_Inst		-4,4956		11,7949		16,6554	*	7,3987	
		(9,9906)		(11,2912)		(8,5235)		(9,2899)	
		0,6578		0,3093		0,0656		0,4356	
ERPsim_Exp		8,5699		13,5225		1,1706		4,7139	
		(7,8653)		(10,4739)		(4,8679)		(5,8900)	
		0,2895		0,2122		0,8125		0,4334	
_cons		67,6998	****	1,9794		1,6008		11,3108	
		(12,6297)		(14,2808)		(8,9961)		(12,0206)	
		0,0000		0,8912		0,8607		0,3585	
N		28		28		28		28	
F		1,2203		2,8917		4,5007		4,7039	
r2		0,2433		0,3241		0,5373		0,4653	
r2_a		-0,0753		0,0396		0,3425		0,2401	
p		0,3397		0,0274		0,0034		0,0027	

*= P<0.1; **= P<0.05; ***= P<0.01; ****= P<0,001

Where BB = useful indicator, well presented; BM = useful indicator poorly presented; MB = useless indicator well presented; MM = useless indicator poorly presented.

Chapitre 4 : Conclusion du mémoire

4.1 Conclusion

L'objectif de ce mémoire était de déterminer de manière expérimentale s'il y a un ordre optimal dans la combinaison d'éléments de formation énactifs et vicariants qui permet de maximiser l'apprentissage et l'efficacité. Pour ce faire, nous avons étudié l'effet de l'ordre de formation sur les résultats d'apprentissage ainsi que sur l'efficacité des apprenants durant la tâche. Ces résultats d'apprentissage ont été évalués grâce à des mesures objectives et des mesures auto-perçues. Globalement, nos résultats semblent indiquer que l'approche qui débute par la formation de type vicariante permet aux apprenants d'être plus efficaces dans la tâche de formation.

4.2 Rappel des principaux résultats et contributions

Les résultats des articles de ce mémoire ont permis de répondre à la question de recherche suivante : dans quel ordre devons-nous combiner les approches vicariante et énactive dans un contexte de formation afin de maximiser l'apprentissage et l'efficacité des apprenants?

Pour ce faire, nous avons formulé les hypothèses suivantes dans le deuxième article en se basant sur la rétroaction sur le premier article que nous avons reçue à la suite de sa présentation à la conférence *Gmunden Retreat on NeuroIS* 2016.

H1A — Débuter la formation par la portion vicariante engendrera de plus grands résultats d'apprentissages objectifs. ***Non supporté***

H1B — Débuter la formation par la portion vicariante engendrera de plus grands résultats d'apprentissages autoperçus. ***Non supporté***

H2A — Débuter la formation par la portion vicariante entrainera une plus grande efficacité de l'apprenant dans la tâche de formation de manière objective. ***Supporté***

H2B — Débuter la formation par la portion vicariante engendrera un plus grand gain en termes de sentiment d'auto-efficacité relatif à la tâche. ***Supporté***

À la lumière de ces résultats, nous recommandons aux créateurs de curriculum d'intégrer les éléments de formation vicariante avant d'incorporer l'approche énactive dans un contexte où les deux doivent être jumelées. Cette approche permet non seulement d'augmenter le gain en sentiment d'auto-efficacité relatif à l'utilisation des tableaux de bord de gestion, mais elle rend également les apprenants plus efficaces de manière objective dans la tâche de formation. De plus, l'augmentation du sentiment d'auto-efficacité a été identifiée dans la littérature comme étant corrélée avec la performance académique et le succès académique (Honicke & Broadbent, 2016).

4.3 Limites et recherches futures

Toutes études possèdent des limites, et celle-ci n'en fait pas exception. Tout d'abord, l'échantillon étudié était limité à des étudiants de niveau universitaire, ce qui nous empêche de pouvoir généraliser les résultats à d'autres types d'utilisateurs de systèmes d'information tels que des professionnels de l'industrie. Deuxièmement, la durée de la formation est une autre limite qui réduit la portée de cette étude. La durée des deux éléments de formation totalisant 30 minutes est loin de représenter le cas typique des cours universitaires de 180 minutes. De plus, puisqu'il n'y a pas eu de suivi post-expérimental, il nous est impossible de prédire les effets de l'ordre de formation sur les résultats d'apprentissage et l'efficacité des apprenants à long terme. Il serait donc intéressant pour des recherches futures de se concentrer sur l'aspect de la rétention des apprentissages en effectuant une étude longitudinale suivant des sujets sur une plus longue période de temps tels qu'un cours universitaire, ou un semestre complet.

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