Flipping the Flipped Classroom: a Study of the Effectiveness of Video Lectures Versus Constructivist Exploration Using Tangible User Interfaces

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Abstract—In this study, we show results that suggest Tangible User Interfaces (TUIs) may be used to prepare students for future learning. In a previous study, we found that students who used interactive tabletops before studying a text significantly outperformed participants who read a text first and used tabletops subsequently. These findings demonstrate that discovery-learning approaches are better suited to TUIs than traditional “tell-and-practice” approaches. In our current effort, we generalize our findings to a different population, a different learning material, and a different topic. In this study, we employ the tangible interface, Combinatorix (Fig. 1), which enables small groups of students to work collaboratively and discover concepts in probability. Our system supports students’ explorations of principles in combinatorics (i.e., permutations and combinations) that serve as foundations for learning about probability. We describe the design of Combinatorix, as well as an experiment that examined the interaction between focused lectures and free exploration. We found that students who first explored the topic on a tangible interface and then watched a video lecture significantly outperformed students who watched a lecture first and then completed a hands-on activity. We discuss how the “functional fixedness” induced by the video lecture limited the students’ learning of probability, and conclude with guidelines for implementing interactive tabletops in classrooms.

Index Terms—Computer-supported collaborative learning, education, input devices and strategies

1 INTRODUCTION

In the debate between traditional and progressive approaches to education, one of the main divisions occurs between instructivists and constructivists [19,23]. The former group advocates structured, scripted, standardized learning environments and materials, while the latter stresses the importance of exploration, construction, and discovery. This debate has been amplified recently with the advent of new constructive technologies such as low-cost educational robotics and digital fabrication [5,36,9], as well as new, easy to learn programming environments [4,26]. Hands-on learning and its derivatives, long time strongholds of progressive education, were suddenly brought back to life, and gained widespread visibility [25]. Thus, more than ever, designing good discovery-learning activities has been the recent focus of many educational researchers and designers. The premise is that students who discover scientific and engineering concepts by themselves create more deep and meaningful knowledge structures [6]. Discovery learning approaches build on constructivist theories [23] and suppose that children and not “tabula rasas” and that learning transpires more efficiently when learners, starting from their previous knowledge, construct new knowledge through interaction with the world rather than through the memorization of facts and procedures. For the past decade, constructivist frameworks have served as guidelines for educators seeking to promote students’ learning in STEM fields. However, even though this approach is theoretically sound, many researchers have found themselves struggling to implement discovery-learning activities in real-world classrooms [19].

Providing the right learning environment with the optimum amount of scaffolding has proved challenging, and a frequent result is that, although some learners would thrive in any discovery-learning environment, many are left confused or frustrated. Thus, there is a need for developing new approaches for designing discovery-based learning activities that cater to all students.
The studies described in this paper seek to fulfill this need. We are proposing to combine new technologies (i.e., Tangible User Interfaces) with existing theoretical frameworks in education (i.e., the “Preparing for Future Learning”, or PFL, framework [32]). The PFL framework was formulated by Bransford and Schwartz [6] after they conducted a series of studies comparing constructivist and instructivist approaches. They found that students who conducted exploratory activities prior to instruction performed better than a control group that only received direct instruction followed by practice exercises. They concluded that preparatory activities did not simply teach a particular concept directly; rather, such activities actually prepared students for future learning. This means that the goal of the discovery activity is better construed as having students explore complex concepts by asking themselves questions and formulating their own theories of the phenomena in question before receiving the standard instruction. When the students listen to a lecture or read a textbook chapter, they can then compare their understandings with the explanation given by an expert. As with constructivist theories, the assumption here is that such interventions promote higher learning gains by permitting students to proceed with acquired personal knowledge, which may be utilized to make sense of their teachers’ explanations. This approach differs from “tell-and-practice” instruction, where teachers first teach the concepts ex cathedra and subsequently provide students with practice exercises.

In a previous study [31], we showed that implementing the “discovery” approach with a tangible interface promoted greater learning gains than did the same learning activities organized and implemented through the “tell-and-practice” method. More specifically, we designed a controlled experiment and taught students about the human visual system. In one condition (“Table-Text”), students interacted with an augmented-reality interactive tabletop where they manipulated a physical small-scale brain and were able to create “virtual” lesions on the visual pathways (Fig. 2). Their goal in this exercise was to understand rules governing visual processing within the human brain. They then read a textbook chapter on the same topic. Students also completed a pre-test before the first activity, a middle-test between the two activities and post-test at the end of the study. In a second condition (“Text-Table”), students completed the exact same activities but in the reverse order: the reading of a textbook chapter was followed by interaction with the tangible interface.

Students in the first group (“Table-Text”) followed a “discover” approach while students in the control group (“Text-Table”) received “tell-and-practice” instruction. The differences were significant: the students in the “Table-Text” group learned 27% more than their peers in the other group (Fig. 3). This shows that most of the current traditional instructional approaches could be vastly improved, because the majority are based on the “tell-and-practice” model. This includes not only standard classroom instruction, but also more recent educational innovations such as video learning platforms, MOOCs, and the “flipped classroom” model, in which student-centered activities follow rather than precede instruction.

**Fig. 1.** Two students using Combinatorix to explore a probability tree. They have positioned the letter “C” on the first placeholder, which reorganizes all possible combinations of the letters “ABCDE” into five groups of equal sizes.

**Fig. 2.** The tangible interface used in the previous study (BrainExplorer). Students manipulated a small-scale brain where the augmented reality system displayed visual pathways between brain regions. Here, the outer left optical radiation is cut (1), which means that the top right corner of the visual field (2) is not perceived by the brain.

**Fig. 3.** The results of the previous study (N=28) [31]. Students learned significantly more when using the TUI in a “discover-first” approach (blue line, “Table-Text”) than in “tell-and-practice” instruction (red line, “Text-Table”).
The previous study led to results that justify a replication. First, we would like to know whether this effect generalizes to other students. We utilized graduate students from a first tier American elite university in the previous study, and it is possible that this population of students is particularly good at finding patterns in an open-ended learning activity. In the current study, we used undergraduate college-level students from an American community college. Secondly, it is possible that this effect is limited to a domain where TUIs facilitate spatial mapping, for which neuroscience is an ideal candidate. In our replication, we focused on a more abstract and traditional topic (probability theory). Thirdly, we do not know if we can use this effect to enhance classroom instruction: in other words, does our manipulation work in cases where teachers lecture in place of students simply reading a textbook chapter? To find answers to these research questions, we used small video lectures for the standard instruction in this study. Our hypothesis was that the effect described above (preparing students for future learning with a tangible interface as opposed to standard “tell-and-practice” instruction) should generalize to another group of students (from a community college), to a different domain (probability theory), and to a different kind of learning medium (video lectures).

1.1 Goals and Contributions
The contribution of this paper goes beyond merely replicating and expanding our previous results. We are tackling a challenging domain in that probability concepts are notoriously difficult to learn under traditional pedagogical regimes; their abstractness and intangibility make them hard to grasp even for college-level students [15]. Probability theory abounds with counter-intuitive notions and paradoxical problems, and students usually find it difficult to utilize prior knowledge of other mathematical domains to make sense of it. More often than not, as the literature has extensively documented, intuitions lead students in the wrong direction (e.g., see the Monty Hall problem). Prior research in teaching STEM disciplines (Science, Technology, Engineering and Mathematics) suggests that open-ended environments can promote students’ learning in ways that traditional instruction cannot [8,23,30]. In particular, this approach offers students much better cognitive and epistemological tools to uncover their own misconceptions [35]. In this effort, we are interested in helping students discover the laws of probability in such environments. In a later section, we will describe a tabletop augmented-reality system with a TUI (tangible user interface [15]) that we designed to scaffold students’ exploration of these concepts.

We believe that testing this kind of system in isolation is not the ideal way to advance current classroom instruction. By isolation, we mean conducting a controlled experiment comparing students’ learning from a lecture (control group) or with a TUI (treatment group). From the perspective of the students utilizing only the interactive tabletop, it is not realistic to assume that they will learn all of probability in an open-ended learning environment. It is more likely that this kind of technological platform will be integrated with standard teaching practices. Thus, it is necessary to explore the interactions between classroom instruction and innovative learning environments before making more general and comprehensive claims about efficiency of the learning environments that emerge through the combination of these separate approaches. In this paper, we take a preliminary step in this direction by determining whether a TUI leads to greater learning gains when used before or after a standard type of instruction (i.e., a lecture). This comparison is of interest beyond the scope of using TUI in classrooms because the latter approach (using a TUI after a lecture, also referred to as a “tell-and-practice” method of instruction) is frequently utilized in most classrooms. Acquiring empirical evidence about which of these two approaches leads to improved learning gains should provide foundational results that teachers, educators, designers, and computer scientists can leverage when constructing the next generation of technology-enhanced hands-on activities. This goal is reflected in our experimental design (section 4.3), where we compare a discovery-based approach with a tell-and-practice type of instruction.

In the following section, we begin by reviewing related research in the teaching of mathematical concepts and the use of a TUI in educational research. Next, discuss the participatory design process used to create Combinatorix, which combines virtual and physical interactions followed by a description of an experiment that examines the appropriate order and timing of focused lectures and free exploration. Finally, we discuss the results and conclude with suggestions for designing tangible interfaces for classroom settings.

2 RELATED WORK
2.1 Misconceptions in Probability
Tversky and Kahneman [38] demonstrated that everyone, even professional statisticians, suffers from systematic biases when making intuitive judgments of probability. Yet understanding probability is essential for dealing with everyday life. Politicians often make policy without understanding the implications of the data available to them, and patients have difficulty interpreting medical test results or evaluating the costs and benefits of a vaccine. Even graduate students who plan to teach mathematics maintain strong misconceptions [13]. More importantly, a number of classic mathematical problems can be seen and solved as probabilistic processes [40]. As a simple illustration, given that “Steve is a very shy and withdrawn person, how likely is Steve to be a farmer, salesman, librarian or physician”? Typically, answers include propositions that take personality traits into account and neglect prior probabilities (i.e. how likely is anyone from the general population to be a librarian or a salesman?). This example reflects one (among many) of the issues that people have when they attempt to think in terms of (Bayesian) probabilities, but default to simple heuristics instead. There are many more examples given by Tversky and Kahneman that illustrate the idea that

http://en.wikipedia.org/wiki/Monty_Hall_problem
probability is a complex and counter-intuitive domain, and not only for Bayesian probabilities.

Given the complexity of probability theory, it should not be surprising that students hold multiple misconceptions when learning about this topic. In high school, Batanero [3] found that teenagers have trouble understanding and applying combinatorial formulas. Common mistakes include double-counting events, confusing the type of events (i.e. undistinguishable versus distinguishable), utilizing non-systematic listing (i.e. solving a problem by trial and error), and faulty interpretation of tree diagrams (e.g. in particular when students produce an incomplete or incorrect diagram). More dramatically, Fischbein and Ditza [12] investigated the evolution of those misconceptions across different age ranges (students in grades 5, 7, 9 and 11): contrary to their hypothesis, they found that most of these misconceptions grew stronger with age. Additionally, it is also surprising is that even professionals dealing with probabilities on an everyday basis hold a variety of misconceptions on the matter. For instance, Jendraszek [16] gave a test to future mathematics teachers at the elementary, secondary, and college levels to measure their understandings of various aspects of probability theory, and she discovered that on average, the rate of correct responses was only 56%. She found that “Participants of all levels showed evidence of the equiprobability bias (miscounting of outcomes in a question concerning two dice), exhibited ignorance of the effect of sample size and were seldom successful on countintuitive conditional probability problems.” (1st page [16]) Thus, at every level there is a need for teaching probability theory in a more integrated and in-depth way.

It should be noted that misconceptions are usually durable and difficult to correct because they are deeply rooted in existing cognitive structures. Over the past decades, researchers have sought to document and correct misconceptions in a variety of ways. Unfortunately, it seems that multiple approaches are needed to accommodate the different domains and age groups, and no method has proven to offer a universal solution. Indeed, most instructional methods attempt to expose students to the “truth” with the hope that doing so will erase their previous erroneous knowledge and replace it with appropriate concepts. However, numerous studies have shown that this approach does not work and that misconceptions are “deep seated and resistant to change” [35]. As a consequence, replacement approaches directly conflict with the constructivist premise that learning is the process of adapting prior knowledge” (p.21). Smith, diSessa, and Roschelle [35] do not provide a unique method to remove all misconceptions from students, but suggest a few ways to correct them in a constructivist fashion. First of all, they propose to leave abstract representations and return to familiar situations when the students are found to hold misconceptions. Indeed, “novices can exhibit expert-like behavior in explaining how a complex but familiar physical system works” and are more likely to revisit their understanding of a concept based on everyday objects and experience. Secondly, they emphasize the importance of using constructive discussions (or collaborative learning, in other terms) as a way to reformulate and re-conceptualize students’ ideas; it is crucial to remove confrontation from the debate and to affirm students’ pre-conceptions as evolving structures capable of refinement. In our project, we paid special attention to prompt prior knowledge from students and support discussion with their peers.

2.2 Teaching Probability in a Constructivist Way

Various attempts at teaching probability in a constructivist fashion have been made. For instance, Abrahamson advocates an “embodied” approach, where students exploit the interaction between their bodies and the physical world to discover mathematical relationships [2]. He designed various ways of physically collecting samples to illustrate concepts in probability (e.g. law of large numbers, normal distributions). One example is the “marble scooper” that he designed and thoroughly tested with different age groups. He also showed how coupling those tangible environments with computer simulations allow students to develop more complex theories about chance [1]. His approach is related to Fast’s [11] attempt at using analogies to make concepts in probability more intuitive. By providing familiar or anchoring situations, Fast’s findings suggest that analogies can prevent the activation of some misconceptions.

Among the more recent constructivist approaches, the “Productive Failure” (PF) framework [18] is particularly relevant in our context. The idea behind PF is that the more students struggle and even fail while attempting to learn a new concept, the more likely they are to recall and apply that knowledge later. This finding implies that too much scaffolding may have a negative effect on learning and that some open-ended exploration of a domain may have positive consequences over the long run. The idea of productive failure as been replicated in many studies, and is currently an accepted theoretical framework in the learning sciences.

In sum, constructivist approaches seem to be a relevant framework for reducing the number of misconceptions held by students studying probability. We were inspired by this previous work and put a special emphasis on open-ended hands-on activities. More specifically, we chose to build our system as an interactive tabletop to support students’ collaborative explorations of the domain. The next section describes how this kind of learning environment supports constructivist activities in small groups.

2.3 How to Support Socio-Constructivist Activities: Interactive Tabloets in Education

The interactive tabletop is currently viewed as an ideal platform for designing constructivist activities. Dillenbourg and Evans [8] mention that “tabletops convey a socio-constructivist flavor: they support small teams that solve problems by exploring multiple solutions. The development of tabletop applications also witnesses the growing importance of face-to-face collaboration in Computer-Supported Collaborative Learning (CSCL) and acknowledges the physicality of learning.” They describe
33 points that educational designers should take into consideration when developing new systems. They also emphasize the impact of tabletops for learning at different levels: cognitively (for individual learners), socially (for small groups), at the classroom level, and institutionally. They advocate that design decisions should be made at a specific level. Also, despite the potential of this technology for college-level education, there is currently a paucity of interactive tabletops currently available for teaching in complex domains.

Previous work in designing educational tabletops informed the design of our system. The Tinker Table [17] is an interactive tabletop on which students of logistics can build small-scale warehouses. The researchers who designed the system found that tangible versions of the system benefited students’ learning beyond what had been achieved by the same system implemented as a multi-touch table [29]. Their work demonstrates the importance of shaping technology to support teachers and illustrates the crucial role of communication between researchers and teachers in the creation of useful and relevant educational technologies [41]. Piper and Hollan [24] conducted a study with undergraduate students, comparing the affordance of tabletop displays and paper handouts for studying college-level neuroanatomy. Their study indicated that the tabletop interface provided benefits for learning, for example by encouraging users to repeat an activity prior to consulting the solutions. Valdes et al. developed and evaluated GreenTouch [39], a collaborative environment for engaging novice students in phylogeny research, which consists of a mobile application for data collection and a tabletop interface for exploratory analysis. While their findings illustrate that tabletop interactions support high-level reasoning and hypothesis testing, they did not measure learning gains directly. Finally, Shaer et al. [34] evaluated Gnome Surfer, a tabletop interface for collaborative exploration of genomic information and deployed it in a college-level neuroscience course. Their work emphasizes the advantages of having students collaborate around a tabletop to conduct open-ended inquiries involving large amounts of heterogeneous information.

These previous attempts at implementing tabletop environments in the classroom are promising in that they support collaborative explorations of scientific domains. We were inspired by these studies and decided to create a similar learning environment for supporting students’ exploration and discovery of probability concepts.

2.4 Design Guidelines

Building upon the prior work described above, we sought to design a tangible interface that supported socioconstructivist activities. More specifically, we focused on building a system in which:

1) Students would be able to interact with a more familiar and concrete representation of the concepts taught (i.e., the tangible interface), instead of the purely abstract and textual material presented in classroom settings.

2) Students could work in small collaborative learning groups, freely explore the domain, and make mistakes that would not bear any negative consequence later on (i.e.: that would permit Productive Failure).

3) Finally, we leveraged the PFL framework and designed an activity that would not directly teach students about probability; rather, the system would prepare students for future learning.

These three guidelines constituted the pillars of our design process. We intended to create a system where small groups of students could potentially fail in a productive manner and where those experiences would prepare them for future learning.

3 Final Design of the Combinatorix Tabletop

Our final design is implemented as a tangible user interface [15], where a camera and a projector are positioned under the table. Tangibles are tagged with fiducial markers, and the camera detects their location using the Reactivision framework [20]. A projector displays additional visualizations around the tangibles to scaffold the learning process. More specifically, three kinds of augmentations are projected:

1) A welcome screen on which users are given ten challenges to solve (Fig. 4, top). The challenge is accompanied by multiple answers and a hint. Examples of challenges include “How many different linear arrangements are there of the letters A, B, C, D, E, for which A must be next to B?”, “How many different linear arrangements are there of the letters A, B, C, D, E, for which E is not last in line?”, “What is the probability of having a combination where A is first and E is before D?”.

2) A probability tree, which adds or removes branches based on users’ actions (Fig. 4, middle). The tree displays the number of possible combinations as well as the results of various constraints (e.g. how many combinations can you form, if letters “A” and “B” have to be next to each other?). This screen was inspired by our participatory design described above and the cardboard prototype we tested with users (Fig. 5).

3) A Venn diagram, illustrating symmetrical relationships (Fig. 4, bottom). The diagram displays all possible combinations and separates them on the basis of specific arrangements (e.g. how many combinations are possible if the letter “A” has to be positioned before the letter “B”?). The answer is 5! / 2, since “A” will precede “B” in half the combinations, and “B” will precede “A” in the remaining combinations. The design of this screen was guided by observations collected during office hours for an introductory computer science division probability class.

Users may switch between representations by turning a cube positioned on the surface of the table. Each face of the cube represents a different screen: e.g. a question mark, a tree, or a Venn diagram. The cube is visible in
Combinatorix supports both student explorations in this problem space and knowledge negotiation in small collaborative learning groups [29]. Previous studies showed that collaboration [34] and conceptual reflections [31] are central components of educational TUIs. More specifically, Combinatorix provides small groups of students an environment where they can experiment with (or even fail to fully understand) concepts in probability in order to prepare them for future learning. As mentioned above, we are interested in unpacking the complementarity of standard classroom instructions and hands-on activities on TUIs based on the PFL [6] and PF frameworks [18].

We contrast two educational positions in our user study [32]. The first, a “tell-and-practice” approach, advocates direct instructions followed by practice exercises. The idea is to expose students to an experts’ lecture, and subsequently to reinforce this first exposition with drilling exercises. The second approach (labeled “inventing”) calls for the provision of carefully designed activities to activate prior knowledge in students, who may then be confronted with an experts’ explanation of a domain. The idea in this case is to have students formulate their own theories of a phenomenon, and, following that, to provide them with an expert’s theoretical explanation. This process allows them to adjust and refine their initial, basic understandings of concepts by incorporating them within the theoretical framework elaborated by the expert. The first approach is widely used in classrooms, while many researchers in the learning sciences advocate the second one [6,23,35].

4 EXPERIMENT

We conducted an experiment to determine whether it is more efficient for students to watch a video lecture before (“video→table” group), or after (“table→video”) engaging in a hands-on activity using an interactive tabletop. Based on the PFL and PF frameworks, we expected students in the “table→video” group to achieve higher learning gains than the students in the “video→table” group.

4.1 Participants

Twenty-seven (N=27) college students took part in this study. Three were run individually and later excluded from our statistical analyses. Six dyads were in the “video→table” group (6 males, 6 females; average age = 23.1, SD = 8.49), and six dyads in the “table→video” group (8 females, 4 males; average age = 21.55, SD = 5.59). Students chose to participate in the study in exchange for class credits. One prerequisite for participation was to have no prior knowledge of combinatorics.

4.2 Material

In the first instructional block, students watched a video segment of a university professor giving a lecture about combinations and permutations. The video was edited from an online recording of an introductory lecture from a freshman course on probability. In the second instructional block, students used an interactive tabletop to go through ten questions about combinatorics and probability. The questions were of increasing difficulty, and the
students were to answer as many as they could. Tangibles and different visualizations (described in the previous sections) were provided to assist students in solving those problems.

Participants in the two experimental groups completed the same pre- and post-tests. The pre-test was a modified version of questions found in an introductory textbook on probability and included the following five questions to evaluate whether participants had prior knowledge in combinatorics: “How many ways can 10 people be seated in a row if... 1) there are no restrictions on the seating arrangement? 2) persons A and B must sit next to each other? 3) there are 5 men and 5 women and no two men nor two women can sit next to each other? 4) there are 5 married couples and each couple must sit together? 5) there are 4 men and they must sit next to each other?”

The post-test was an abridged version of the first homework provided in an introductory probability course and consisted of the 10 questions listed below, which extended the challenges on the interactive tabletop from 5 letters to the entire alphabet: “How many different linear arrangements are there of the alphabet (26 letters)... 1) in total? 2) for which A and B are next to each other? 3) for which A is before B? 4) for which E is last in line? 5) for which E is not last in line? 6) with 10 placeholders? 7) with 10 placeholders if the order doesn’t matter? 8) what is the probability of having a combination where A is first and E is before D? 9) if you form two combinations (each time starting with a full set), what is the probability that the first one has a D in the second place and a C in the last place? 10) if you select three letters (out of 26), what is the probability of having A, C, and E in your final combination (where the order doesn’t matter)?” Finally, the video lecture came from the course mentioned above, and featured a renowned professor from a first tier university who received several awards for the quality of his teaching.

4.3 Design

We used a between-subjects AB/BA crossover design for this study (Fig. 5). Groups of two students were introduced to the task for the first 5 minutes, and then either worked on the interactive tabletop or watched a video lecture for the following 15 minutes. Next, they completed a second task (e.g. watch the video lecture if they worked on Combinatorix, or work on Combinatorix if they watch the video lecture) for an equal amount of time (15 min.). Next, they took a 10-minute post-test to evaluate their learning gains, and finally the experimenter debriefed them.

4.4 Measures

Students’ learning gains were measured by pre- and post-tests (described in the “Material” section). We coded the quality of student collaboration using the Meier, Spada, and Rummel [22] coding scheme, which is commonly utilized in the CSCL community because of its high inter-rater reliability, consistency, and validity. Episodes of collaboration were rated on a 5-point scale across nine dimensions (sustaining mutual understanding, dialogue management, information pooling, reaching consensus, task division, task management, technical coordination, reciprocal interaction, and individual task orientation). Finally, we gathered automated log data during the tabletop activity (e.g. tangible added, moved, removed, and number of times a visualization was displayed).

Fig. 5. Experiment design: we used an AB / BA between-subjects design. “Table” refers to students working on Combinatorix; “Video” refers to students watching a video lecture.

We also analyzed students’ discourse during their interactions with the interactive tabletop. We categorized their utterances in four main categories: Miscellaneous (comments that did not belong to any other category; e.g. “I haven’t taken a math class in years”), read instructions (students merely reading the screen), short comment (comment that does not contribute to the conceptual discussion; e.g. “Let’s go to the tree diagram,” “Okay!” “Let’s try answer 2”) and conceptual comments (remarks that contribute directly to solving the problem at hand; e.g. “I think that answer 3 is correct because you need to multiply by the number of objects you can choose for this placeholder,” “I think that you need to divide by two”, “this answer is too small to be correct”).

4.5 Procedure

Participants were run in dyads in a private room. Upon arrival, the experimenter welcomed them and thanked them for their participation. The experimenter also described the goal and procedure of the experiment and asked them if they had any questions. They then sat at two different tables and completed the pre-test. After 10 minutes, the experimenter collected the tests and asked the participants to sit at the interactive tabletop on the other side of the room. Depending upon their experimental group, they either watched a brief video lecture or interacted with Combinatorix for 15 minutes. In both instructional blocks, the experimenter provided the participants with the same instructions (i.e. “please collaboratively explore the material in front of you”). For the tabletop condition, the experimenter also gave a brief overview of the interaction techniques the participants could use to interact with the system. At the end of the 15 minutes, the experimenter switched the activity and repeated the instructions as necessary. Finally, after the participants completed the two blocks, they were asked to fill
a post-test evaluating their learning gains. The experimenter collected the tests after 10 minutes and debriefed the participants.

5 RESULTS

5.1 Learning Gains

We computed learning gains by subtracting students’ scores on the pre-test from their scores on the post-test. The pre-test confirmed that no student had prior knowledge in combinatorics (Fig. 6): no student scored higher than 10%. The scores in the post-test support the main hypothesis: Students who completed a hands-on activity on an interactive tabletop and then watched a mini-lecture significantly outperformed students who watched the lecture before completing the hands-on activity: F(1,22) = 9.28, p < 0.01, Cohen’s d = 1.61 (mean for the “video→table” group = 2.23, SD = 1.77, the “table→video” group = 4.23, SD = 1.42). This effect remained significant when computed at the dyad level: F(1,10) = 7.73, p < 0.05.

5.2 Accuracy on the Task

There was no significant difference between the two experimental groups in terms of their task performance (i.e., solving the challenges presented on Combinatorix): F(1,10) < 1, p = 0.74 (percentage of correct answers for the “table→video” group: mean = 0.35, SD = 0.25. For the “video→table” group: mean = 0.30, SD = 0.20). There was also no statistically significant difference in terms of the number of challenges answered: F(1,10) < 1, p = 0.44 (for the “table→video” group: mean = 6.67, SD = 2.16. For the “video→table” group: mean = 5.67, SD = 2.16).

5.3 Patterns of Collaboration

Overall, students in the “table→video” group had a higher quality of collaboration; however, this difference is not significant: F(1,10) = 2.51, p = 0.14. But since the number of groups in each condition is rather small (N = 12 in total), it is possible that this difference would be significant with more participants. Moreover, the effect size is large (Cohen’s d = 0.96), which suggests that there is, in fact, a significant difference. Interestingly, the total collaboration score correlates positively with higher learning gains: r(12) = 0.63, p < 0.05. Since the number of groups is small, we also report results where the effect size is large and p < 0.1 (Fig. 7).

We found that students in the “table→video” group scored higher in the following dimensions: task orientation (“each participant actively engages in finding a good solution to the problem, thus bringing his or her knowledge and skills to bear”) F(1,10) = 4.72, p = 0.055 (effect size = 1.29), reciprocal interaction (“Partners treat each other with respect and encourage one another to contribute their opinions and perspectives. Critical remarks are constructive and factual”) F(1,10) = 7.14, p = 0.023 (effect size = 1.77) and technical coordination (“Partners master the technical skills that allow them to use the technical tools to their advantage”) F(1,10) = 3.77, p = 0.081 (effect size = 1.15). This suggests that students in the “table→video” group were more focused on the task, interacted more equally, and took better advantage of the TUI.

5.4 Students’ Exploration

We also looked at the number of actions performed by each group: the number of tangibles added and removed on the tabletop, as well as the number of times they accessed a particular visualization. The three screens are described in Fig. 4: the top image shows the “questions” screen, the middle image shows the tree visualization, and the bottom image shows the Venn diagram.

Our log files suggest that participants in the “table→video” condition tried more combinations of tangibles than participants in the “video→table” condition. However, those differences are not significant: F(1,10) < 1 (Fig. 8, right side). Interestingly (Fig. 8 – left side), participants in the “table→video” group also accessed the Venn diagram visualization more often: F(1,10) = 17.07, p < 0.01. This difference was also significant for the number
of times the first screen (i.e. displaying the questions) was displayed: F(1,10) = 6.00, p < 0.05. Interestingly, the number of times students displayed the third screen (i.e. the Venn diagram) was positively correlated with higher learning gains: r(12) = 0.63, p < 0.05.

5.5 Discourse Analysis

The results of our discourse analysis confirm the trend found in the previous section. Students in the “table→video” condition produced more utterances in general. In particular, they generated more conceptual comments (Fig. 9) according to the coding scheme described in the Methods section (section 4.4).

We found a significant difference for the number of short comments F(1,22) = 7.44, p < 0.05 and the number of conceptual comments F(1,22) = 7.15, p < 0.05. Students who watched a lecture before working on the interactive tabletop produced fewer comments in general, both on the conceptual and non-conceptual levels. Conceptual discussion was strongly correlated with a positive learning gain: r(24) = 0.7, p < 0.001.

While coding the videos, we also categorized the screens on which students produced conceptual comments. The only significant difference is on screen two (the tree visualization): students in the “table→video” group had more conceptual discussions than the students in the “video→table” group: F(1,22) = 18.83, p < 0.001. This measure was also correlated with a positive learning gain: r(24) = 0.64, p < 0.05.

5.6 Qualitative Results

We conducted an additional analysis of our videos, this time with a qualitative approach. We cursorily reviewed the videos seeking episodes that might explain the differences in the learning gains of our two experimental groups, and we describe here the most striking difference. First we exhibit an episode from a dyad in the “video→table” group followed by an episode from the “table→video” group. In the two excerpts, students are working on problem 3, “How many different linear arrangements are there of the letters A, B, C, D, E, for which A is before B?” The possible answers are: “a) 5! / 2, b) 5! / 3!, c) 1/26, d) 5! / 4! + 3!, e) None of those answers.”

<table>
<thead>
<tr>
<th>Dyad in the “video → table” group (excerpt length: 4:10 min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ Starts at 6:20 min ]</td>
</tr>
<tr>
<td>- Hem... so why don’t we do a process of elimination then?</td>
</tr>
<tr>
<td>- So it's not going to be this one.</td>
</tr>
<tr>
<td>- I agree</td>
</tr>
<tr>
<td>- And I don’t think it would be 1/26, because...</td>
</tr>
<tr>
<td>- It’s just not the right number</td>
</tr>
<tr>
<td>- Right [ laugels ].</td>
</tr>
<tr>
<td>- I don’t know... I feel like there has to be like... you know what I’m saying</td>
</tr>
<tr>
<td>- Yeah, me too... sort some of equation</td>
</tr>
<tr>
<td>- N over r.</td>
</tr>
<tr>
<td>- Minus r?</td>
</tr>
<tr>
<td>- So n is 5, r is one, 5 over 1... plus r?</td>
</tr>
<tr>
<td>- Okay so it’ll be n, which is 5, over r, which is, what did you say? one?</td>
</tr>
<tr>
<td>- Yeah because they are taking [ inaudible ]. I don’t know!</td>
</tr>
</tbody>
</table>
- It would be $r$ factorial times $n$.
- Okay. So five factorial over 4 factorial? Yes? Oh no. No, no. It would be 1 factorial times four! Right? So five times three times two times one. So one times two... [laughing].
- Okay. [laughs]
- Because if it would be this [pointing at an answer], then that means that three would be the denominator, three factorial, and then... so that would be $r$ factorial which is one factorial... and then... the rest was what, $n - r$?
- I think so.
- So $n - r$ would be four, right? Because 5 minus 1.
- Yeah.
- five minus one is four, so the bottom would be $r$ factorial, parentheses, four, close parentheses.
- So... is $r$ gonna be one?
- I don't know... we choose that, but I don't know...
- I'm wondering, because... maybe it could be two?
- Because there are two letters?
- Yes.
- Okay well then if it's two, then it's two factorial times $n$ minus... which is three. Well then that would be that one. That would be the second one. You see?
- But... so it would be five factorial over $r$, which is two, so two factorial times...
- five minus two, which is three.
- Yeah. So... do you see?
- two factorial times three?
- I don't know...
- But that would be six, two factorial times three. Right? Because two times one is two: times three, six. Yeah...
- So it's none?
- I think so...? [laughs]
- Okay [grabs the cube]. Do we agree? [She grabs the cube to select the corresponding answer, as shown below.]
- Yes [laughs].
- [ends at 10 min 30 sec]

Students proceed to select “None of those answers are correct,” which is wrong. The total number of combination is 5!, and half of those combinations have A before B, and the other half have B before A. This is a symmetry problem that can be explored with the treemap visualization.

It is striking to see that the students were focusing purely on recalling and applying one particular formula that they saw during the video lecture. It is also clear that they did not fully understand the formula because it is not the correct one to use in this context. The fact that they were focusing on this particular piece of information prevented them from exploring the resources offered by the interface: they looked at the visualizations at the beginning of the activity and quickly dismissed them. They probably spent a considerable amount of time on this formula because it “looked like” the answer (a factorial divided by an integer). In other words, they misconstrued superficial features of this formula as relevant to their quest for a solution [4]. In total, they completed 6 out the 10 challenges and got 3 of those 6 correct (50%).

We now turn to a dyad from the “table → video” group. This group completed eight out of the 10 challenges and got five of them correct (62.5%) during the activity. They immediately recognized the deep structure of the problem and used the correct representation to solve it. They struggled for a few seconds because the treemap did not display any number, but one student had an insight and realized that the problem space was evenly separated (that is, there was the same number of combinations on each side of the treemap). This insight led them to choose the correct answer, and they were quickly able to move on to the next question.

Dyad in the “table → video” group (excerpt length: 45 sec)

[Starts at 4:05 min]
- [Reads the problem] How many different linear arrangements are there of the letters A, B, C, D, E, for which A is before B? Now we get to do the Venn diagram [they tried before, but realized that it wasn’t helpful for the question that they were trying to answer].
- Uh uh. Where A is before B...
- [Positions the letters A and B on the table.]
- What? [The visualization divides the number of combinations by two with a treemap as shown below – students call it a Venn diagram.]

- But that doesn't show us how many, does it?
- No.
- No. Oh wait... it's half! [She splits the combinations in two with her hand, as shown below.]
- What?
- It’s half! It looks like it... let’s go back to the question to see our options. [They use the cube to go back to the first question.] So... the first one. That’s what the diagram shows.
- The first one? Oh yeah, divided by two. Okay! [ends at 5:50]

Students proceed to select the first answer “5! / 2,” which is correct.

Compared to the “text→table” group, those students were more likely to answer more questions and were more accurate in their answers. They also completed the study with higher learning gains.

We found evidence of similar types of behavior in other “video→table” groups. For example, students in group 13 kept referring to the structure of the equation they saw in the video (participant 26: “So it must be five factorial divided by something”). In group 8, students used technical terms mentioned by the teacher (participant 7: “You don’t have to order [them] before other variables”), which wasn’t apparent in other groups. The same group also expressed opinions about their math abilities (“I’m not really good at math either”), which seemed to be reinforced by a typical “school” mindset introduced by the video.

Students in the “table→video” group, on the other hand, were more likely to work with the visualizations and exploit them to answer the challenges. For instance, the following dialogue illustrates how group 11 explored the probability tree and discussed how locking a letter in one spot produces 24 combinations (4!): “Do you mind if I click on the little tree?; sure, go ahead; So C would have 24 [combinations], right? So we have five choices and each just have 24. Yeah. So pretty much five times 24, right? Do you agree?; I mean, yeah. Yeah.”). The last utterances show how students attempted to reconstruct the formula for factorials by interacting with the tree visualization (i.e., 5 * 24 is actually 5 * 4 * 3 * 2 * 1, which is the same as 5!)

These excerpts, which were typical throughout the data, suggest that students in the “table→video” condition were more likely to exploit the resources offered to them and that students in the “video→table” were more likely to refer to the video to solve the challenges on the tangible interface.

This qualitative analysis provides preliminary answers regarding the significant difference between student learning gains for these two conditions. It seems that students in the “video→table” group were primed to memorize, recall, and apply formulas from the video lectures to solve the challenges presented on the tabletop. On the other hand, students in the “table→video” used different types of epistemological resources [27]; they utilized their own initial knowledge about how the system should work, took advantage of the visualizations provided by Combinatorix, and were, thus, primed to see those as spaces for exploration and sense-making, which helped them answer questions more accurately.

6 DISCUSSION

Our results support the PFL (Preparing for Future Learning) [6] approach to integrating new educational technologies to the classroom. In comparison, the tell-and-practice (“video→table”) approach produced significantly lower learning gains. More specifically, we found that groups of students who worked collaboratively on an interactive tabletop and then watched a video lecture outperformed students who first watched the lecture and then completed hands-on activity on Combinatorix. We also observed that the two groups utilized markedly different types of epistemological resources [27]. We interpret this result as evidence that TUIs can complement classroom instruction if their exploration comes before direct instruction, eliciting the correct use of students’ previous knowledge and empowering them to create their own explanations before formal instruction. These findings replicate previous results [31] in which we showed that individuals who learned from a TUI first and subsequently read a textbook chapter outperformed students who completed these activities in the reverse order. This study is a first step toward generalizing our results to two different domains (neuroscience and probability theory), two different populations (students from a first-tier university and a community college) and two different instructional materials (a textbook and a video lecture). We agree that this study cannot by itself substantiate the claim that the effect found in these cases applies to very different domains and to students from different ages and backgrounds, or for different time frames (e.g., learning activities that extend beyond an hour of instruction). Further replications will be necessary to make that claim. We actually conducted a third study [28] that replicated this effect, and used additional measures to understand its mechanisms. In this case, we found that participants in the “table→text” condition were more likely to develop more refined mental models, to become more curious and more engaged, and to perceive themselves as being more successful (compared to the students in the “tell-and-practice” group). Additionally, these differences are associated with higher learning gains. This suggests that the “tell-and-practice” sequence may have detrimental effects on students’ learning, but also that the “explore → lecture” sequence may have beneficial effects on
students’ engagement and on the refinement of their mental models.

The present study was not merely a replication of the forgoing investigation because a number of new metrics and theoretical frameworks were introduced. In particular, we were concerned about the impact on collaboration, and indeed participants in the “table→video” group had a much higher quality of collaboration. In particular, students were more engaged in the task, made more efforts to encourage one another to contribute their opinions and perspectives, and they more fully took advantage of the technological tools available to them. On the other hand, study results suggest that students tended to be less willing to engage themselves in a conceptual discussion about probability when the hands-on activity followed a video lecture. Thus, it may be beneficial to organize collaborative learning activities before delivering a lecture. These findings are especially useful for instructional designers because most classroom activities follow the opposite sequence: first students are told what they need to know, and then they are put in small groups to practice their understanding of the concepts already taught.

Students in the “table→video” group also explored the problem space to a greater extent and accessed the visualizations provided to them more often. Additionally, our discourse analysis suggests that students talked more when utilizing the tabletop prior to watching the video lecture. More importantly, they spent more time on conceptual discussions about probabilities. A finer analysis showed that the students’ discourse on the second screen (the tree diagram) was significantly higher for this group and highly correlated with a positive learning gain. Combined with the results stated above, this development suggests that students in the “table→video” group were more active and more willing to explore the resources provided to them.

One potential explanation of this difference, illustrated in our qualitative analysis, is what cognitive psychology terms, “Function Fixedness”; in a classic experiment, Dunker [10] asked subjects to attach a candle to a wall so that it would not drip onto the table below. They were provided with a candle, a box of thumbtacks, and a book of matches. Dunker found that very few subjects considered using the inside of the box as a candle-holder; instead, they attempted to attach the candle directly onto the wall with the tacks. He called this effect “mental fixedness,” which he defined as a “mental block against using an object in a new way that is required to solve a problem.” We believe that school-like lectures can act as “mental blocks” against students’ creative understanding of a domain: they work extremely well in certain contexts (e.g. for passing standardized tests or solving word problems), but they have detrimental consequences in situations where students must demonstrate cognitive flexibility or transfer their understanding of a concept to a different situation [6]. In our experiments, we saw that students reduced their exploration of the available resources to focus on question answering. One interpretation, supported by our qualitative analysis, is that the video lecture put students in a “school” mindset: this standard instruction acted as a mental block against exploiting visualizations and manipulating physical objects to scaffold their understanding of a domain, and primed to students to try to find formulas and memorized information. This interpretation is supported by another very significant body of work in the learning sciences: the idea of manifold epistemological resources [28]. Rosenberg et al. showed that depending on the structure of a classroom activity, students are primed either to rely mostly upon knowledge delivered by “authority” (teachers, books, formulas, etc.), or to build upon their own knowledge, even if initially this knowledge is incomplete. The authors showed dramatic gains for students who trusted what they already knew in order to solve a new type of problem. Our qualitative analysis shows very similar results, although with a new type of priming: students in the “video→table” tended to use knowledge delivered by authority and start from formulas to solve a problem, even if they did not understand the meaning of the formulas. Students in the “table→video” group, conversely, were primed to start from their own knowledge and used the system to build a coherent argument.

This study has a number of limitations. First, the learning gains are significant, but relatively small. This is explained by the great difficulty of the test; we chose to ask challenging questions to avoid a ceiling effect and to achieve a dataset with a broad distribution. Additionally, our evaluation does not test the effectiveness of our system as a stand-alone learning tool. We chose this experimental design because 30 minutes offers very little time to learn about a domain of this complexity. We believe that our current results serve better to provide insights for the implementation of interactive tabletops in classroom settings than as a direct comparison of the effectiveness of this approach against other methodologies. Another limitation is that our sample is relatively small; running more subjects would provide more reliable data than the results reported above. However, we consider our small sample size to be a minor limitation because we are replicating a previous result. Moreover, we found a large effect size between our two experimental conditions. When we combine both studies, we have 52 data points (28 participants from [31] and 24 participants reported in this paper), which suggests that TUIs increase learning gains when used before (rather than after) traditional instructions. This makes us relatively confident that we are capturing a real effect and not just noise. It should also be noted that studies with a similar sample size are common in education and HCI, especially for exploratory work. Finally, for space and focus considerations, our qualitative analysis was preliminary and did not encompass all the groups in our study. Rather, we used an opportunistic approach and sought to highlight the most striking difference between our two experimental conditions by drawing on samples of representative students. Future work should involve more thorough investigations to determine whether an easing up of the mental fixedness effect uncovered in our study is responsible for students’ higher learning gains as well as for their use of manifold epistemological resources.
7. CONCLUSION

Our findings suggest that innovative technologies can have radically different effects on students’ learning outcomes contingent upon how they are integrated with traditional teaching practices. Choosing the wrong sequence of activities may impede students’ learning, whereas adopting a constructivist perspective is likely to foster knowledge building. In this study we were able to replicate previous results which showed that TUIs increased students’ learning gains when used as a discovery-learning tool prior to traditional instruction (as opposed to a tell-and-practice approach, which reversed this sequence). These results have implications for a wide range of educational approaches (e.g., classroom instruction, flipped classrooms, MOOCs). When correctly designed and implemented, TUIs can boost students’ learning by preparing them for future learning [31], providing them with a fertile soil for socio-constructivist activities [6], supporting their exploration of a problem space [29], and by increasing their engagement in hands-on tasks [30].

Since this study is a replication of previous results (and not merely an isolated data set), we can claim with greater confidence that the PFL framework is a promising way to shape the design of educational TUIs in STEM domains. Our results suggest that the “tell-and-practice” approach popularized by Skinner and other behaviorists [33] can be outperformed by a combination of recent learning theories and innovative technologies. We do not claim that the approach described in this paper offers a universal methodology for teaching all STEM theories; it is more likely to be appropriate for teaching counter-intuitive concepts, but less so for gaining proficiency in the use of procedural knowledge. Finally, our work is a departure from recent educational innovations: MOOCs, video-based learning platforms, and many implementations of “flipped classrooms” tend to reinforce rather than challenge the Skinnerian mindset. They favor quick tell-and-practice instructional sequences through mini-lectures and quizzes. We believe that a reconsideration of this approach is in order. For the learning of more abstract and less accessible material, a constructivist mindset is likely to benefit students’ learning.

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