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PAPER

Using a Random Controlled Trial to Explore the Impact of AI-Enabled Learning

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ABSTRACT

Much is being made of AI's role in learning. However, there have been few studies that evaluate AI's ability to make learning more efficient or more effective and specifically the learner's willingness to embrace and use AI-enabled learning tools over conventional learning methodologies. Working with a manufacturing company, we used a randomized control trial approach (matching pairs) to present two groups of employees with a course on design thinking, one presented via a traditional learning management system (LMS Group) and other through an AI-enabled tool (AI Group) that adapts the content based on the learner's demonstration of knowledge, with the content being identical in order to compare completion rates, time to completion, learning outcomes (subject matter knowledge retained) and the learner's perceptions of value and experience. We also were able to compare the AI-enabled version of the course to the same version with the addition of a face-to-face instructional component. While we found that those participants in the AI-enabled Group completed the course in a shorter period of time, had better learning outcomes and expressed higher perceptions of course value, the AI-enabled Group significantly underperformed the LMS Group in terms of course commencement and completion rates. Our findings suggest that the adoption of AI-enabled learning tools may follow similar patterns of adoption rates of new technologies – and require educating learners regarding the use, benefits, value and limitations of new AI-enabled tools before widespread acceptance and usage.

KEYWORDS

corporate learning, adaptive learning, randomized controlled trials, AI & learning

1 INTRODUCTION

The integration of artificial intelligence (AI) in education has been a subject of increasing interest and research. Specifically, AI's application in corporate education has gained attention as organizations seek more efficient and personalized training methods to upskill and reskill workers. This article explores the use of a randomized controlled trial (RCT) to study the effectiveness of AI in corporate education,

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providing insights into AI's potential impact on learning outcomes and employee training. RCT's are widely accepted as the gold standard in social science evaluation and the best approach to allow for any sort of causal inference. In RCT's, there is a treatment group (in our case, AI-Enabled) and a control group (traditional LMS) and learners are randomly assigned to one of the groups to ensure that other possible causes of a treatment are minimized or eliminated.

The adoption of AI in corporate training has gained considerable attention in recent years. The potential benefits of using AI for companies and their employees include: increased productivity by automating time consuming administrative tasks and providing learning professionals more time to focus on more important work such as curriculum design; development of corporate training programs and course materials; personalization of learning (based on employee learning styles, pace and individual needs) at scale across organizations, within departments and/or based on employee-specific roles or responsibilities; increased employee engagement and motivation due to more engaging training environments (such as virtual reality) versus traditional training methodologies; immediate and actionable assessments of learning knowledge, progress and skills gaps with personalized learning pathways for individual courses of study and remediation; more intelligent data analytics producing actionable insights and more effective and efficient training programs; and reduced costs [1].

2 MATERIALS AND METHODS

But despite the popular press touting the benefits and perils of AI, little research has been done on the actual use of AI for training and its effect on learning outcomes. Jarrahi et al. [2] have explored the development of AI-powered chatbots and virtual assistants to provide personalized learning experiences and these tools have been shown to facilitate employee engagement and knowledge retention. Research by Boyd et al. [3] has demonstrated the application of reinforcement learning techniques in corporate training. Using simulated environments, employees can practice and improve their skills without the need for physical resources, which has the potential to significantly reduce training costs and increase scalability [4, 5, 6].

Efforts such as Danner et al's [7] study have highlighted the importance of transparency, fairness, and accountability in AI-powered training systems. These findings emphasize the need for responsible AI development and implementation in corporate settings. Studies also have shown that timely support can enhance problem-solving skills and reduce the time required to master new concepts [8, 9, 10]. In addition, work by Alkhuraiji et al. [11] has shown that AI can personalize training content based on individual learner performance; and that this approach enhances the efficiency of corporate training by focusing on the specific needs and abilities of each employee.

RCTs in Corporate Training: There have been few studies that use a RCT to explore the efficacy of AI in supporting corporate training. Man et al. [12] compared the performance of employees who received AI-assisted training with those who underwent traditional training methods. The RCT revealed a significant improvement in skills acquisition and a shorter time to proficiency among the AI-assisted group. Other RCTs have demonstrated that personalized learning using AI can tailor learning content and course pace to individual learners and lead to improved knowledge acquisition and retention [13, 14]. In addition, AI has been used to create adaptive learning environments that adjust difficulty levels based on a learner's performance; and RCTs have revealed that adaptive learning leads to better engagement and motivation among corporate learners [15].

A study by Vonderlin et al [16] examined RCT studies in mindfulness and found that mindfulness programs led to significantly improved customer satisfaction scores. And in a study by Paul et al. [17], medical students who received flipped classrooms modules outperformed those who received traditional in-person training.

2.1 The benefits of an RCT

The benefits of conducting RCTs in corporate training could include:

- Causality and Rigor: RCTs establish causal relationships between training interventions and outcomes, providing reliable evidence for decision-making.
- Objectivity: RCTs minimize bias by randomly assigning participants, reducing the risk of confounding variables that may affect the results.
- Data-Driven Decision-Making: RCTs generate empirical data that informs the development and improvement of corporate training programs.
- Customization: RCTs allow organizations to tailor training programs based on empirical evidence, increasing their relevance and effectiveness.

Despite the advantages, conducting RCTs in corporate training can be resource-intensive and time-consuming; and ensuring participant compliance and ethical considerations are additional challenges [18, 19].

Research Design: The corporation ("company sponsor") we worked with is a mid-cap company with approximately 8,000 employees globally. It defines itself as a precision technology company and falls within the manufacturing sector and broadly speaking the manufacturing of synthetic fibers and plastics. The company sponsor has several North American Industry Classification Codes due to a number of corporate acquisitions in several industries.

As a randomized control trial is the gold standard when it comes to inferring efficacy using experimental research design [20], we wanted to design a RCT that would allow us to compare the use of an AI-enabled system against a traditional training program by randomly assigning learners to either an AI-assisted learning group or a control group utilizing traditional training methods. This design allows for a rigorous assessment of the causal impact of AI on education outcomes.

Concurrently, the company sponsor wanted to conduct a hybrid (Hybrid) program (online and supplemented by face-to-face interactions) and use the AI-enabled technology to deliver the asynchronous training program to that group. In effect, we simply viewed the addition of this group as a serendipitous opportunity to compare behaviors in use between two groups who were provided with the exact same learning content.

2.2 Participants

A third-party vendor provided the AI technology through a subscription license and the company sponsor agreed to purchase 75 licenses for the RTC. We therefore elected to attempt to enlist 150 employees of the company sponsor into the study, which roughly aligns with the academic literature on acceptable sample sizes for a population of 8,000 [21]. The company sponsor sent out emails to all employees inviting them to sign up for the course without telling them anything about the use of the AI technology; employees were simply informed that they would help the company evaluate the course.

The company sponsor chose the 20 participants for the Hybrid program, all of whom were in a sales role at the company. This group was mandated to participate in the program. The other 129 participants self-selected to participate in the study. Recognizing that it is common practice to have different sample sizes, we matched 55 pairs based on geography and job function, inferring that these were the two best known variables that might account for variance in endowments or performance. This is based on the idea that English fluency can be influenced by location and that people in different job functions may be more likely to be educated and/or know more about innovation. The remaining 19 participants were assigned to the control group.

2.3 Content/Module

Our objective was to control for content in the program design. We worked with a subject matter expert who is a professor at a top ranked U.S. based business school to build the learning modules for the program. The modules are focused on innovation and based on a graduate level course taught by the subject matter expert; and we used the exact same learning content for each group in our study.

2.4 Technology

We chose a widely used AI-enabled adaptive platform in which to build the AI-enabled program; and we used one of the most commonly used industry standard learning management systems for the control group. This was the system the company sponsor was already using to deliver training to its employees. We assume the reader is familiar with a traditional LMS that delivers content – largely videos and content modules – in a linear format where the learner completes one module and then moves on to the next one. The AI-enable adaptive platform, by contrast, starts by probing the learner about her knowledge of a topic and then, depending on the level of knowledge demonstrated, delivers the corresponding content. If the learner demonstrates knowledge of the content, she moves through the content very quickly; but if she is struggling with the content, the AI-enabled tool presents the content at a slower pace and in more in depth, constantly probing for demonstration of understanding. The result is a potential non-linear path with significant variation in times of completion whereas in a traditional LMS time is always fixed but the learners' understanding of the content varies.

All the modules were built to Tin Can/xAPI standards and used videos of the subject matter expert combined with PowerPoint slides designed by the expert. All videos were between 5–7 minutes in duration with the overall course being 180 minutes of content. Post-test questions were delivered in each of the platforms, as each has the capacity for embedded assessments. To be clear, we are not evaluating the underlying content or the course design. A reasonable educator could argue using Bloom Taxonomy that presentation of content and knowledge testing is not ideal. We are simply testing the impact of the AI on the course – when using the same content/course design.

2.5 Instruments/Measures

We used commonly accepted approaches to evaluate training, broadly aligned with Kirkpatrick [22] although we did not ordinally rank the approaches. We endeavored to measure experience/perceptions which is the generally accepted standard [23].

Knowledge. We worked with our subject matter expert to design assessments to test for knowledge, again commonly accepted as the appropriate approach [22]. The pre and post-tests were based on the assessments our subject matter expert uses in her graduate level course. The assessments were not in any way psychometrically validated and were designed solely to test for knowledge and understanding of the material.

Perception. To capture the learners' perceptions and experiences (rather than to build and validate new instruments), we elected to use questions pulled from commonly used instruments to evaluate e-learning and, in discussions with the company sponsor, selected questions that were of interest to the sponsor and probed perceptions of experiences, usefulness, quality, and relevance [24, 25, 26].

Time on task & completion rates. Both the AI-enabled platform and the standard learning management system automatically calculated both the time spent on the course and who started but did not complete the course. We were able to determine the number of participants in the study who never started the course based on those employees who were enrolled on a platform but never began the course.

2.6 Empirical approach

For each variable, a mean was calculated and for comparison purposes we used the test statistic for a two-sample independent t-test (commonly known as a "2 sample t test") which allows us to compare the means of two groups and calculate whether their difference is statistically significant. This is calculated by taking the difference in the two sample means and dividing by either the pooled variance or the estimated standard error. The estimated standard error is an aggregate measure of the amount of variation in both groups. If the difference between the means is statistically different, it means that the results from the two groups is different. This is a very common approach in randomized controlled trials in the social sciences [27].

3 RESULTS

We first will present the findings from our RCT and then the findings from our review of the Hybrid program.

3.1 AI vs. Non-AI: findings related to learning & behaviors

We had 55 participants enrolled in the AI-enabled course versus 74 participants in the traditional course. All of these participants were randomized after matching on two characteristics – job role and geographic location. Below we present a table that compares the two groups in terms of their behaviors.

Item	AI-Enabled	Traditional
Number	55	74
Percent Never Started+	45%	14%
Percent Started But Did Not Complete	25%	28%
Percent Completed+	29%	58%
Average Time Spent in Course+	149 min.	194 min.
Knowledge Growth+	30%	17%

Note: +statistically significant difference between the means.

A lower number of employees participated in the AI-enabled course because of license limits and the need to put the Hybrid learners in that group. However, having different sample sizes when doing a 2-sample t test is generally acceptable. [28] Using this approach also allows us to compare the Hybrid course to the AI-enabled course, although that comparison is not randomized and, consequently, we must be cautious in our interpretation of the results.

We find that when looking at the two groups, the learners using the AI-enabled course spent significantly less time learning (almost 45 minutes less in a course that is roughly three hours long). We find there is no difference between the two groups when comparing the percentage of learners who started but did not finish the course – but there is a significant difference between the assigned group and those who completed the course which is almost exclusively attributable to the fact that significantly fewer learners assigned to the AI-enabled course began the course (45% versus 14%).

In terms of knowledge growth measured as the change between the pre and post-test, we find that there was a significantly different outcome in that the AI-enabled group improved by 30% whereas the control group only improved by 17%.

3.2 AI vs. Non-AI: findings related to perceptions

Perception	AI-Enabled	Traditional
Satisfied with Experience+	91%	53%
Better than other E-learning+	75%	42%
Content Interesting	92%	84%
Content Relevant+	92%	79%

Note: +statistically significant difference between the means.

In terms of learner perceptions of the experience and its use, both groups found the content interesting and there was no statistical difference in the two groups' perceptions of the experience.

However, the comparison of all the other perceptions between the two groups were statistically significant. Participants in the AI-enabled group much more satisfied with the experience (91% vs. 53%), and they thought the experience was better than other e-learning experiences (75% for the AI group versus 42%

for the control group); and perhaps, most interestingly, given that the content delivered to the two groups was exactly the same, the AI-enabled group found the content significantly more relevant when compared to the control group (92% versus 79%). Finally, overall, when compared to other studies that have used these perception instruments, both groups perceived the experience more positively [29, 30].

3.3 AI vs. Hybrid findings related to learning & behaviors

Item	AI-Enabled	Hybrid
Number	55	20
% Never started	45%	15%
% Not completed	25%	30%
% Completed	29%	55%
AVG Time (min)	149	159

We need to be quite cautious when attempting to interpret the AI-enabled versus the Hybrid results for several reasons. First, the Hybrid group was selected by the company sponsor and mandatorily assigned to participate in the program whereas the AI-enabled group self-selected to participate in the program. Secondly, all employees in the Hybrid group have essentially the same job function. And any analysis here is further complicated by the fact that the groups are not the same size, so any statistical comparison of the means is not reliable. We also did not pre and post-test the Hybrid group for knowledge (at the company sponsor's request).

That said, the average time for each group to complete the course is much closer than the average time the traditional group took to complete the course which makes intuitive sense since both the AI-enabled and the Hybrid groups are using the same technology.

Interestingly, the percentage of participants in the Hybrid group that did not start the training was lower than the percentage of participants in the AI-enabled group that did not start the training, resulting in a higher (almost double) completion rate. This, we believe, could be attributed to either the fact that: the participants in the Hybrid group were mandated to attend the training program versus the AI-enabled group that volunteered to participate, which aligns with the literature on persistence in corporate training [31]; or that the participants in the Hybrid group had to be in a room with their peers and the professor for a classroom session and that served as a catalyst to completion, which aligns with the literature on peer effects [32].

4 DISCUSSION

In terms of behaviors and knowledge, most of the findings from this study align with what we would expect to find based on the academic literature. Participants in the AI-enabled program had almost double the knowledge growth when compared to participants in the traditional training program. Other studies focused on adaptive and personalized learning had similar outcomes [33, 34].

With respect to time on task, the findings again were consistent with other research findings [35]. The AI-enabled course took an average of 23% fewer minutes to complete. This generally happens because the system adapts to the learner; we also generally see wider variance in time to completion.

In terms of perception, both groups described the content as interesting which makes sense given that exact same content was used for both groups. In addition, the group using the AI-enabled course reported a much more favorable experience which is again generally consistent with the literature and is theorized to be primarily a function of the pacing [36]. What is curious and warrants further research is that employees taking the AI-enabled course had a markedly better perception of the usefulness of the material. We are not aware of any studies that would explain why the exact same material would be perceived as more useful.

What we found most curious were the findings in terms of adoption and completion rates, where the traditional learning methodology clearly outperformed the AI-enabled version. Simply put, employees were much less likely to begin the newer format than the format of learning they were familiar with. This is similar in concept to the pencil metaphor proposed by Lindy McKeown which in itself was based on Crossing the Chasm which hypothesized that there is an adoption lifecycle for technology. The chasm is the space between the early market and the mainstream market. It begins with innovators, who are at the bleeding edge of technology adoption. This can be compounded by what the economic historian Paul David noted – that having a technology itself isn't enough to ensure widespread and useful adoption [37].

When we compare the Hybrid program to the online only program, we did see a significant improvement in terms of adoption rates and consequently completion rates. It is unclear to us if it is Hybrid design or selection bias (as employees in the Hybrid program were required to participate and had the same job function). There are studies that find Hybrid programs consistently outperform their online only counterparts [38]. There is also research showing that accountability measures such as mandating training or attendance in a classroom can improve completion rates [39].

5 CONCLUSION

Based on our research, we conclude that AI-enabled learning technology has the potential to improve corporate training both from an employer's and the employees' perspective as measured by time on task, knowledge growth and overall user satisfaction/experience, which we believe will lead to increased employee engagement and the motivation to learn new skills.

However, corporate learning professionals need to be mindful of the reluctance of employees to use new and unknow technologies; and these professionals need to develop plans to educate learners regarding the use and benefits of these new technologies. The next frontier in corporate training may well be the personalization of learning (based on employee learning styles, individual needs, specific roles or responsibilities), real time assessments and personalized learning pathways for individual courses of study and remediation. But to get there, employees need to understand and be willing to use the technology.

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