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The More, the Better: Evaluating the Effects of a Three-Year Multi-Course Financial Education Intervention

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Using an RCT experimental design, this study analyzed the effects of a three-year, multi-course financial education program on a group of upper middle school students recruited online. The impact of the fully digitized courses was evaluated at the end of the study and six months after the program completion. Results of repeated measure mixed linear model estimation showed that compared to the single-course alternative, the multi-course intervention was significantly more effective in increasing students' confidence in their basic financial skills, and the effect remained six months post-intervention. Although no effect of the intervention on the reported financial behaviors was found immediately after the program, the participants who took multiple courses started to show improvement six months after the intervention. The analysis also found that the multi-course intervention, though not leading to more conversations between the participants and their parents on financial topics, prevented the decline of communication which was observed among those who took only one course. Taking a single course on fundamental financial literacy topics such as saving, budgeting, and investing had a short-term impact on students' financial knowledge, which completely diminished by the end of the intervention.

Keywords: Financial education, teenagers, experimental design, longitudinal study, multi-course intervention

Introduction

Currently, facing an overwhelming number of complex financial and economic situations, many young people are unprepared to make informed financial choices as they move into adulthood. Academic literature on the state of financial capability has been very clear regarding the alarmingly low financial literacy among future generations, with only about 10% of 15-year-olds achieving high proficiency (OECD, 2022). Financial literacy scores have been found to be directly correlated with an individual's financial wellness. Compared to Gen Z, members of Gen Y are three times more likely to have even one month of expenses stored in non-retirement savings (TIAA/ GFLEC, 2022). Recognizing that the habits adolescents form at young age can often shape financial behaviors in adulthood (Lusardi, 2019), many programs have been developed which focus on improving the financial capability of younger people. In general, studies have shown positive effects of early financial education on adolescents' financial knowledge, attitude and behaviors (Amagir, Groot, van den Brink & Wilschut, 2018).

Despite the generally positive effects found in the literature, a few issues in early financial education and its impact analysis should also be noted. First, although many studies detected

positive changes immediately after program completion, there is mixed evidence for effects in the middle and long run. The few studies which do examine post-intervention effects tend to focus on financial behaviors (Rehman & Mia, 2024), while the middle and long-term effects of financial education on financial knowledge and self-efficacy are much less researched. Second, while most research focuses on school-based programs, home-based financial education where students can receive the education in a more natural and relaxing setting and where parents are actively involved can be an important supplement or, in some cases, enhance the formal education at school (Moreno-Herrero, Salas-Velasco & Sanchez-Campillo, 2018). Nevertheless, few studies provide empirical evidence to show if home-based financial education indeed leads to significant improvement in learners' financial capability. Last, but not least, although intensive financial capability programs which last for a longer time and have more sessions have been shown to generally lead to better learning outcomes (Lusardi, Michaud & Mitchell, 2020; Choudhary & Jain, 2023), there are not many studies which test whether increasing program intensity also benefits adolescent students. These teenager students are more prone to the diminishing returns of increasing intensity (Kaiser & Menkhoff, 2017) as they may not have faced that many financial situations in their life to contextualize and internalize what they learn in the courses.

Considering the existing research and its limitations, this study examined the effects of a six-course intervention lasting for three years on adolescent learners and analyzed how those who took multiple courses differentiated from those who only took one introductory financial literacy course in their financial knowledge, self-efficacy and reported behaviors. To create an intensive educational experience without overwhelming the students, participants of the study only needed to finish one assigned course within a two-month course window in each semester from Fall 2021 to Spring 2024. Participants were allowed to take the fully digitized courses online and at home. Apart from the survey immediately after students finished each course, a follow-up survey was conducted six months after the last course window to test if the effects of the courses still existed after the program concluded.

Literature Review

In general, studies have found compelling evidence which shows that financial education can significantly increase adolescents' financial capability. Increased financial knowledge is one of the most well-documented effects of financial education. Kaiser, Lusardi, Menkhoff and Urban (2022) conducted a thorough meta-analysis of 76 RCT studies examining the effects of financial education programs. They found the programs, on average, had positive, causal treatment effects on financial knowledge and downstream behaviors with meaningful sample sizes, even considering the potential publication bias that studies with significant findings are more likely to be submitted to journals for publication.

Increased financial self-efficacy is also recognized as a positive outcome of financial education. As a multi-facet term, financial self-efficacy, in general, refers to the level of confidence people have in their ability to manage their personal finances and deal with various financial situations to achieve their financial goals (Farrell, Fry & Risse, 2016). Heckman and Grable (2011) conducted one of the first empirical studies on financial self-efficacy. The path analysis showed that increasing financial knowledge significantly increased the students' confidence in dealing with personal financial issues. More recently, Brady, Miller, Balmuth, D'Ambrosio and Coughlin (2021) analyzed a national survey of student loan borrowers in the US and found that those with higher

perceived financial literacy on loans and debt were significantly more confident that they could manage their student loans in a responsible manner.

Financial behavioral change is undoubtedly the most heavily researched area in financial literacy studies. Kaiser and Menkhoff (2020) conducted a review of 37 experimental studies examining the effects of school-based financial education and concluded that there was a small but significant average treatment effect of school-based programs on fostering desirable financial behaviors such as saving, budgeting and healthy credit behaviors. A more comprehensive systematic literature review by Kaiser, Lusardi, Menkhoff and Urban (2022) showed a robust effect of financial education on some financial behaviors (such as saving and budgeting), but less certain on other behaviors (such as insurance and healthy credit behaviors).

The Sustainability of Financial Education's Effects

Although many studies have shown the positive effects of financial education on financial knowledge, attitudes, and behaviors, the longevity of the effect remains unclear. Fernandes, Lynch and Netemeyer (2014) conducted a meta-analysis of 168 academic studies on the effect of financial education, and the findings suggested that most programs ceased to generate sizable impacts within 20 months after the intervention.

The sustainability of the effect seems to vary based on the types of behaviors measured and the age of the audience. The study by Collins (2013) tracked low-income families who were assigned to receive financial education in a housing program for 12 months. The participants had less risky credit behaviors during and shortly after the study. However, only reported behaviors were found to have improved 12 months after the program with no sizable actual behavioral changes were detected. Another study by Frisanchio (2023) provided conflicting evidence. The credit and repayment behaviors of a group of high school students were checked using the data from the local credit bureau three years after they received in-class financial education. Although much smaller than the effect observed immediately after the intervention, a significantly positive effect still existed. Recognizing the need to test the post-intervention effects of financial education programs, in this study, a follow-up survey was conducted six months after the last course window.

Besides the effects of financial education, there is also a growing body of research into the optimal forms of financial education. The following sections review the literature on two major discussions which are relevant to the current study.

Continuous Financial Education

Although most studies reviewed are evaluations of individual programs, there is growing recognition that continuous financial education is crucial to bring about behavioral changes. Fan and Zhang (2021) examined the data from over 17,000 individuals, they found positive behavioral changes (i.e., setting up emergency savings) were more likely to take place when education occurred at multiple venues (e.g., at home and at school) and through different life stages (e.g., from students to emerging adults) such that the positive changes caused by education of different sources can reinforce each other. The study by Wagner and Walstad (2019) provided more evidence on why continuous financial education that lasts from high school to adulthood is necessary for maintaining financial health. Examining a sample of over 22,545 individuals, they tested the differentiated effects of high school, college and on-the-job financial education. While financial education received later in one's life led to more desirable changes in behaviors that had more

imminent consequences, such as credit card and mortgage payment, early financial education was a stronger predictor for desirable financial behaviors which may not have had immediate consequences, such as having an emergency fund and making financial investments.

The importance of continuous financial education can also be examined from a program intensity perspective. Measuring retirement saving behavior, Lusardi, Michaud and Mitchell (2020) found that intensive programs with follow-up sessions after the primary instruction led to an increase in saving for retirement which lasted long after program completion, while one-time programs only had short-term effects. Choudhary and Jain (2023) conducted a systematic literature review of studies about financial literacy education programs for marginalized women. The 22 studies they examined revealed that programs with longer duration (6 months to 3 years) and follow-up sessions were more effective in fostering healthy financial behaviors such as account opening and saving.

Recognizing the value of continuous financial education, this study created an intervention which consisted of six financial education courses that adolescent participants were asked to take over a three-year period. By comparing the effect of the multi-course program to that of a single-course alternative and a control group, this study tested if the more intensive program could generate better learning outcomes. This replicates the prior research shown in adult populations.

Home-Based Financial Education

Another area which receives increasing attention in financial literacy literature is the value of financial education outside of the school setting. Although school-based programs have been shown to be effective in increasing students' financial knowledge and behaviors (Kaiser & Menkhoff, 2020), there may be unique advantages in home-based financial education.

Gudmunson and Danes (2011) conceptualized financial socialization as a type of process in which individuals form attitudes, values, perceptions, and behaviors regarding financial matters by observing, modelling, modifying and learning from the people and environments around them. They also posited that family interactions could profoundly influence the financial capability of young people. The comprehensive review of the literature on financial socialization by LeBaron and Kelley (2021) showed that, despite the increasing availability of various financial education resources, parents are still the primary source for their children's financial learning.

While the critical role of parental involvement in financial education has been heavily discussed, quantitative evidence is limited. A key study by Maldonado, De Witte, and Declercq (2022) compared the learning outcomes of two financial education models: classroom intervention with parental involvement in homework and homework alone. The findings showed that although classroom intervention alone was already effective, having parental involvement at home further increased students' financial literacy by 0.38 standard deviation. Another empirical study conducted by Jorgensen and Savla (2010) showed that high levels of perceived parental involvement (i.e., how much the students feel that their parents were involved in their financial education) contributed to the formation of healthy financial attitudes and indirectly led to desirable financial behaviors. This finding suggested that the emotional support students feel in their financial learning could be a factor underlying the benefits of home-based financial education.

Given the importance of parental involvement in adolescents' financial education and the lack of empirical studies to show its value, the current study asked the participants to take the assigned courses at home to create a relaxing learning environment so that the participants could freely discuss the course content and financial matters with their parents. The study also explicitly

measured the effect of the program on student-parent communication on financial topics to test if the home-based program could encourage financial socialization with parents.

Methodology

The Sample

The participants were recruited from 567 parents with 7th or 8th grade children in Fall 2021 who confirmed their interest in participating by submitting a signup form on the study webpage. Each parent was allowed to sign up one child for this study from their family and all children signed the assent form before being included in the study. Initially, 350 children were randomly selected from 567 families, but five did not complete the baseline survey and were not included in the final sample. Each family was assured of \$500 incentives each year after they finished the assigned courses and surveys from 2021 to 2024.

Among the 345 participants, 49% were in the 7th grade and 51% were in the 8th grade when the study began. There were more female participants (53%) than male participants (46%). While Hispanic/Latino students were slightly underrepresented in our sample, Black/African American students were overrepresented. In general, the percentage of students of color in the sample matched the race/ethnicity composition of the U.S K12 student population. Compared to the US general population, more parents in this study received a bachelor's or higher degree (88%). The average annual household income of the sample was between \$100,000 to \$149,999 and in line with the average household income of \$120,000 of American families with children (US Census Bureau, 2022). When the study ended in Summer 2024, 276 participants remained in the study, and the demographic characteristics and baseline outcomes of the remaining participants were not significantly different from those of the initial sample.

Study Procedure

To analyze the effects of the courses, participants were randomly assigned to one of the four condition groups:

Group 1: Participants took all six financial educational courses designed for middle school and high school students. After they finished the basic introductory course in Fall 2021, the participants continued to take five more courses on advanced topics such as banking applications, investing and business finance in the following semesters.

Group 2: Participants only took the basic introductory course at the beginning of the study and were only surveyed afterwards.

Group 3: Participants took all the courses except for the first introductory course.

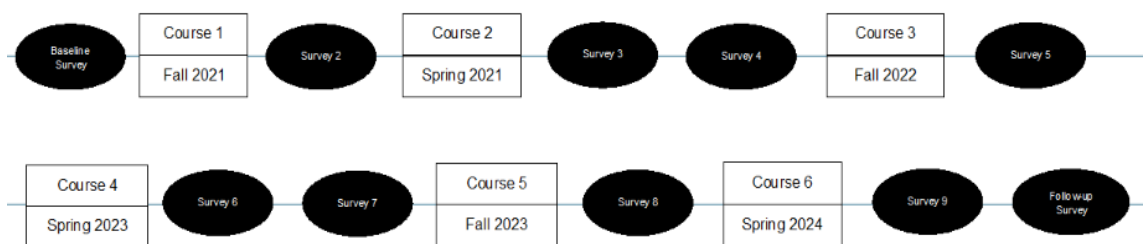
Group 4: This group served as the control group, and participants did not take any course and were only surveyed during the study.

After the random assignment, 30% of the 345 participants were in Group 1, 26% were in Group 2, 28% were in Group 3, and 16% were in Group 4. According to the baseline survey responses, the four groups did not differ significantly from each other in their starting financial knowledge, self-efficacy, or behaviors. By the end of study, 276 participants remained. The group distribution

of the 276 participants was 28% in Group 1, 28% in Group 2, 27% in Group 3 and 17% in Group 4. Attrition was not found significantly different among the four condition groups. We also compared the baseline outcomes and demographics of the 276 remaining students against those of the initial 345 participants, and no significant differences were detected. Therefore, severe attrition bias is unlikely.

The timeline of the study is provided in the chart below. All participants took the baseline survey in Summer 2021 and starting in Fall 2021, participants in the treatment groups took one course in a two-month window in each of the following semesters at home, followed by a financial capability survey (in-study survey) about their financial knowledge, attitudes and behaviors. There was a two-month interval between each in-study survey during which time the students took the assigned courses except for survey 4 and survey 7 which the participants took after the summer break without taking any courses. Given the profound influence of parents on their children, the parents also took surveys about their financial knowledge, attitudes and behaviors in each survey window, and the measures were included in the analysis as covariates.

Figure 1
Timeline of the Study



In total, the participants took nine financial capability surveys during the study (in-study surveys). A follow-up survey was conducted six months after the last in-study survey to test the effects of the program after content conclusion. Although tracking the students for even longer, as Frisancho (2023) did in the analysis of credit card repayment behaviors, could reveal more information on the long-term effects of the intervention; it also imposes several challenges. First, the longer the interval between the last activity and the survey, the more participants would leave the study, which decreases the sample size and power of the analysis. Second, as the participants grew up, more incidents could happen in their life which can potentially impact their financial behaviors but are difficult to measure and control for in the study, decreasing the validity of statistical testing. Therefore, the six-month gap was selected as a compromise between the need for post-intervention effect evaluation and research validity and feasibility.

The Course Overview

The financial educational programs used in the study are six digital courses designed by a leading online education company in the US for middle school and high school students. Students could finish all courses online by themselves without any assistance. Students assigned to the courses took one course each semester from Fall 2021 to Spring 2024 at home without the supervision of the researchers. Participants were given a two-month window in each semester to

complete all modules of each course. The total screen time to finish each course varies from 1.5 hours to 2.5 hours. The topics covered by the courses included:

- Basic financial literacy knowledge such as interest rate, saving and credit
- Introduction to financial investment
- Banking applications and account management
- Basic business finance and entrepreneurship
- Financing higher education plans

It is worth noting that all six courses used in this study were designed for and, in most cases, used by students at school as part of their financial education curriculum. Since this study allowed the participants to use each one of them at home and study at their own pace for two months in each semester from 2021 to 2024, the findings can shed light on whether financial education programs designed for school use can achieve the intended learning outcomes if they are used at home.

The Measurements

To measure the effects of the courses, a comprehensive survey that evaluated the students' financial knowledge, self-efficacy and behaviors was administered immediately before and after each course window. The main measurements for the students included the following items:

Financial Knowledge

The financial knowledge of the students was tested using a simplified version of the *Test of Financial Knowledge for upper middle school or lower high school students* developed by the Council for Economic Education (2016). The internal consistency of the assessment tool was tested, and a high scale reliability was found (Cronbach's alpha = 0.77). The 19-question test covers the following essential financial topics:

- Jobs and Income
- Buying Goods and Services
- Saving
- Credit
- Financial Investing
- Protecting and Insuring

Financial Self-Efficacy

The financial self-efficacy measurement for students evaluates how much confidence the students have in performing essential financial tasks suitable for their age such as making financial plans and managing a savings account (1 = Not confident at all, 5 = Extremely confident). The measurement has been used and validated in the published study conducted by Johnson, Spraggon, Stevenson, Levine and Mancari (2021). Our data confirms the high reliability of the measurement (Cronbach's alpha = 0.82).

Financial Behaviors

The 4-item scale developed and validated by Chowa and Despard (2014) was adopted in this study to measure the financial behaviors of the participants. Specifically, the frequency that students engaged in desirable financial behaviors such as tracking their monthly expenses, creating a budget, saving money for long-term goals and investing, were gauged in the survey (1 = Never, 5 = Very often). The scale had satisfactory reliability (Cronbach's alpha = 0.71).

Student-Parent Communications

Given that money-related conversations during adolescence are one of the strongest predictors for financial capability in adulthood (Jorgensen, Rappleyea, Schweichler, Fang, & Moran, 2017), a special type of behavior, the frequency that the students had conversations with their parents about financial topics at home, was measured in this study. Students were asked how often they had conversations with their parents on important financial topics (1 = Never, 5 = Very often), such as how to use their money, long-term financial goals and career and education planning. The 6-item scale had a high reliability of 0.84.

The survey also asked about the students' demographic information (age, race and grade) and previous experience with financial education (0 = No, 1 = Yes). The participants were also asked to rate the interest they had in the study as a proxy for how serious they were taking the courses and surveys. The participants' parents were surveyed about their financial knowledge, self-efficacy and behaviors. These were all included in the model as control variables.

Statistical Method

This study used the repeated measure mixed model method (RMM) to evaluate the impact of the courses where the time points were used as the within-subjects factor. The intercepts and time effects were allowed to vary for individuals to account for the correlated nature of the measured outcomes of the same subjects over time. Specifically, the joint test of the interaction between group assignments and time was examined to show if the change over time varied for different groups. In addition, the post-hoc test of trends was conducted as a supplementary analysis to show the differentiated change trajectories across the groups. In cases where both the treatment group and control groups showed significant trends in the same direction, the 50% confidence interval overlap rule developed by Cumming (2009) was used to determine if the change in the treatment groups was significantly larger than that of the control group. The CI overlap rule is a common method used to determine if two estimated values are significantly different. When the upper limit of one 95% CI is lower than 50% of one leg of the other 95% CI, the two values are different at about 0.95 significance level ($p = 0.05$). All statistical analyses were conducted using the STATA 17 software package.

The main purpose of the study was to examine the differentiated impact of taking multiple courses versus one course. Therefore, although the students were surveyed before and after each course window, the analysis mainly focused on the changes observed immediately after the program ended (Survey 9), followed by an additional analysis of the change from Survey 9 to the follow-up survey students took six months later. Figures showing learning outcomes immediately following each intervention for each group can be found in the appendix.

Analysis and Results

Financial Knowledge

The baseline survey showed that the students' financial literacy scores were very low before the study began, as the average test score was only 32/100 (SD = 17.3), as shown in Table 1. Model 1 tested the change from the baseline survey to the last financial capability survey immediately after the last course window. Model 2 tested data from the baseline survey to the follow-up survey. The high Wald λ^2 values showed that the set of variables included in the model were jointly significant. The LR test results showed that the RMM method fits the data significantly better than the simple linear model. Although the ICC for both models were relatively low, they were significantly different from 0. The random component estimation also showed significant differences in both the intercepts and the change over time for different individuals. Therefore, adding a random component improved the overall model fit.

Table 1
RMM Estimation Results for Financial Knowledge

	Model 1 (baseline – survey 9)	Model 2 (survey 9 - follow-up survey)
Group		
<i>Group 1</i>	-3.09	2.83
<i>Group 2</i>	-3.73	0.58
<i>Group 3</i>	-2.08	4.07
Post (reference group = baseline survey in Model 1, = survey 9 in Model 2)	2.91	2.24
Group*Post joint test	$\lambda^2 = 1.54, p > 0.05$	$\lambda^2 = 1.25, p > 0.05$
Household income	-0.49	-0.58
Married	-1.85	-1.01
Grade	3.4 *	2.8
Male	6.57 **	7.84 **
White	4.45 *	12.2 **
Knowledge parent	0.13 **	0.11 *
Behavior parent	2.24	0.09
Efficacy parent	-0.43	-1.01
Student interest	2.43*	1.36
Constant	-11.43	0.54
Random components		
<i>Std (constant)</i>	10.31 (95% CI: 8.03 – 13.22)	4.41 (95% CI: 0.03 – 11.56)
<i>Std (time)</i>	1.59 (95% CI: 1.25 – 2.04)	1.96 (95% CI: 1.02 – 3.81)
Wald λ^2	358.85, $p < 0.01$	60.37, $p < 0.01$
LR test vs. linear model	$\lambda^2 = 42.13, p < 0.01$	$\lambda^2 = 150.79, p < 0.01$
ICC	0.36	0.33

Note: * $p < 0.05$, ** $p < 0.01$. Student demographics, the annual income of the households and parents' financial knowledge, attitudes and behaviors were added in the model as covariates.

As the insignificant interaction term in Model 1 indicated, after students finished the courses, the change in their financial literacy test scores did not differ significantly from that of the control group. In fact, the post-hoc trend analysis (see Table 2 below) shows that the scores of those who took the courses and those who did not both increased significantly, and the size of improvement was not significantly different from one another. Therefore, the intervention did not seem to have an immediate impact on students' financial knowledge.

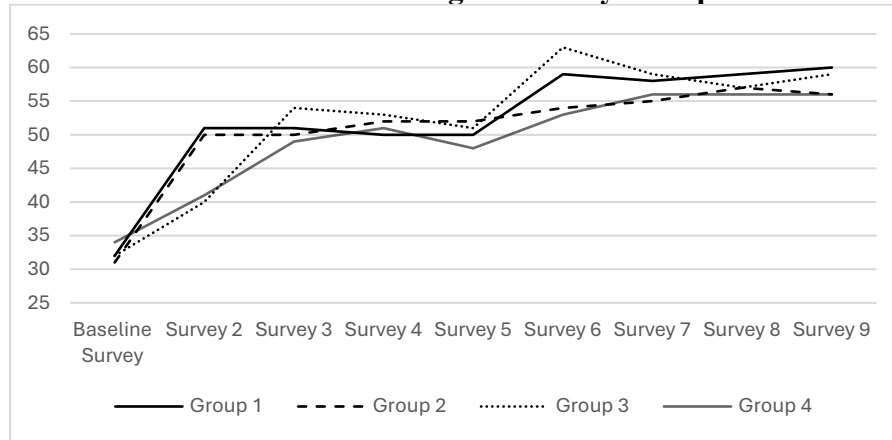
Table 2
Post-hoc Trend Analysis for Financial Knowledge by Group (Baseline – Survey 9)

	Linear Trend	z	p> z	95% CI	
Group 1	13.49	8.79	0.00	10.48	16.50
Group 2	12.32	8.32	0.00	9.41	15.22
Group 3	12.72	8.4	0.00	9.75	15.69
Group 4	10.70	5.6	0.00	6.96	14.45

Model 2 and trend analysis showed that six months after the students took survey 9, there were no significant changes in the participants' financial knowledge scores, and those who took multiple courses during the study did not perform better than those who took only one course or did not take any courses.

The insignificant effect of the courses on students' financial knowledge might be explained by several factors. Particularly, given the time points used in the analysis, the short-term impact of courses taken earlier in the study was not shown. To illustrate, Figure 2 below shows the changes in the test scores for all four groups over the entire course of the study. Although in the end, the four groups did not differ significantly in their test scores, at several points during the study (e.g., survey 2, survey 3 and survey 6), it was clear that students who took the course at those times had significantly larger improvement in their test scores than the control group. In addition, the last two courses students took during the study covered topics about banking applications and financing higher education, while the test instrument employed in the study focused on more standard financial literacy topics such as interest rate, budgeting and saving. As a result, the knowledge students learned from the later courses might not have been fully tested by the assessment.

Figure 2
Financial Knowledge Scores by Groups



Note: The predicted values were shown in the figure.

Financial Self-Efficacy

In general, the participants felt quite confident in their basic financial skills before the program started, as the average self-efficacy score was 3.3/5 (SD = 0.86). By the end of the program (Survey 9), the self-efficacy of those who took multiple courses (Group 1 and Group 3) increased significantly to 4.3/5. The confidence of the students who did not take any course or took only the introductory course also increased but by a lesser degree to 3.8/5. As shown in the table below, the joint test for the significance of the *time*group* interaction indicated that the changes over time varied for different groups.

Table 3
RMM Estimation Results for Financial Self-Efficacy

	Model 1 (baseline – survey 9)	Model 2 (survey 9 - follow-up survey)
Group		
Group 1	-0.01**	0.42**
Group 2	-0.18	0.05
Group 3	-0.06**	0.45**
Post (reference group = baseline survey in Model 1, = survey 9 in Model 2)	0.29*	-0.07
Group*Post joint test	$\lambda^2 = 11.36, p < 0.01$	$\lambda^2 = 0.73, p > 0.05$
Household income	-0.02	-0.03
Married	-0.12	-0.19 *
Grade	0.18 *	0.12
Male	0.14	0.06
White	0.04	0.08
Knowledge_parent	0.002	0.001
Behavior_parent	0.08	0.01
Efficacy_parent	0.06	-0.06 *
Student interest	0.25**	0.15**
Constant	1.58 **	0.54
Random components		

<i>Std (constant)</i>	0.39 (95% CI: 0.31 – 0.49)	0.55 (95% CI: 0.49 – 0.60)
Wald λ^2	324.58, p < 0.01	102.19, p < 0.01
LR test vs. linear model	$\lambda^2 = 19.39$, p < 0.01	$\lambda^2 = 224.35$, p < 0.01
ICC	0.38	0.77

Note: * $p < 0.05$, ** $p < 0.01$. Student demographics, the annual income of the households and parents' financial knowledge, attitudes and behaviors were added in the model as covariates. Based on both AIC and BIC, models without random time effect have better goodness of fit. Therefore, the models only allow the intercepts to vary for individuals.

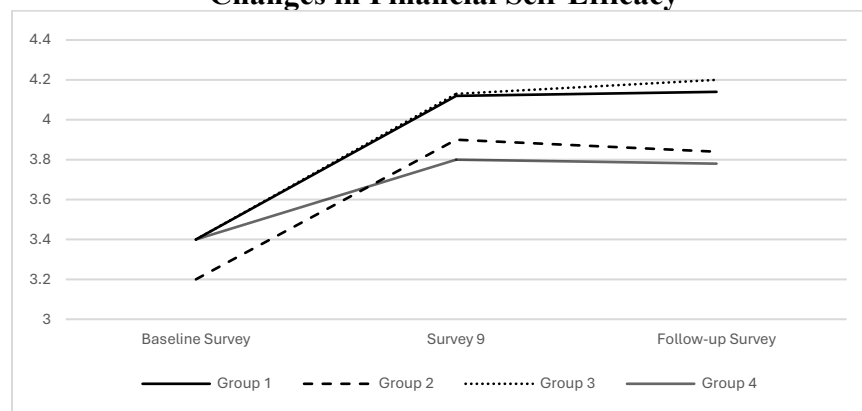
To further test how the change in students' confidence varied across the groups, the post-hoc test of trend was conducted, and a clear difference in the change was detected. The test results are summarized in the table below.

Table 4
Post-Hoc Trend Analysis for Financial Self-Efficacy by Group

	Linear Trend	z	p > z	95% CI	
Group 1	0.39	7.04	0.00	0.28	0.50
Group 2	0.30	5.63	0.00	0.20	0.41
Group 3	0.43	7.76	0.00	0.32	0.54
Group 4	0.17	2.38	0.017	0.03	0.30

From the baseline survey to the last financial capability survey (Survey 9), all groups became significantly more confident in their financial skills. However, based on the 50% CI overlap test, the change of Group 2 was not significantly different from that of the control group, while the changes in both Group 1 and Group 3 were significantly larger than that of the control group. Therefore, the analysis suggested that taking multiple courses significantly increased students' financial confidence, while taking only one course did not have this effect. Group 1 and Group 3 did not have significant differences in the size of their improvement.

Figure 3
Changes in Financial Self-Efficacy



Note: The predicted values were shown in the figure.

As Model 2 shows, the *group*post* interaction for the follow-up period was not significant. Thus, there was no significant difference among the groups in how the confidence level changed six months after the intervention. Nevertheless, those who took multiple courses (Group 1 and

Group 3) were still significantly more confident than those who took only one course or no courses, as shown in Figure 3. According to this finding, it can be concluded that the effects of taking multiple courses remained for at least six months after the last in-study survey.

Table 5
RMM Estimation Results for Financial Behaviors

	Model 1 (baseline – survey 9)	Model 2 (survey 9 - follow-up survey)
Group		
Group 1	0.08	0.19
Group 2	-0.18	-0.06
Group 3	-0.05	0.11
Post (reference group = baseline survey in Model 1, = survey 9 in Model 2)	0.38*	0.09
Group*Post joint test	$\lambda^2 = 1.29, p > 0.05$	$\lambda^2 = 2.76, p > 0.05$
Household income	0.03	0.06
Married	-0.03	0.01
Grade	0.03	0.09
Male	0.02	0.03
White	-0.06	0.04
Knowledge parent	0.001	0.001
Behavior parent	0.31**	0.11*
Efficacy parent	-0.06	0.1
Student interest	0.22**	0.23**
Constant	1.26	1.84 *
Random components		
<i>Std (constant)</i>	0.45 (95% CI: 0.35 – 0.59)	0.71 (95% CI: 0.63 – 0.79)
Wald λ^2	158.28, $p < 0.01$	67.16, $p < 0.01$
LR test vs. linear model	$\lambda^2 = 15.26, p < 0.01$	$\lambda^2 = 122.15, p < 0.01$
ICC	0.35	0.62

*Note: * $p < 0.05$, ** $p < 0.01$. Student demographics, the annual income of the households and parents' financial knowledge, attitudes and behaviors were added in the model as covariates. Based on both AIC and BIC, models without random time effect have better goodness of fit. Therefore, the models only allow the intercepts to vary for individuals.*

Financial Behaviors

According to baseline survey responses, the participants reported that they did not often engage in desirable healthy financial behaviors, as the average financial health score was only 2.6/5 (SD = 0.96), and only a little over one third of the participants engaged in the desirable financial behaviors “often” or “very often”. Like the case of financial self-efficacy, from baseline survey to Survey 9, the financial behaviors of students in all groups improved, but the changes were not significantly different across the groups, as indicated by the insignificant *group * time* interaction in Table 5. Thus, the courses did not seem to have an immediate effect on students' financial behaviors.

The change after the students took the last course was further examined and compared to that of those who took only one course or no courses. As Table 6 shows, the behaviors of the participants who took multiple courses, i.e., Group 1 ($\beta = 0.13, p < 0.05$) and Group 3 ($\beta = 0.12, p$

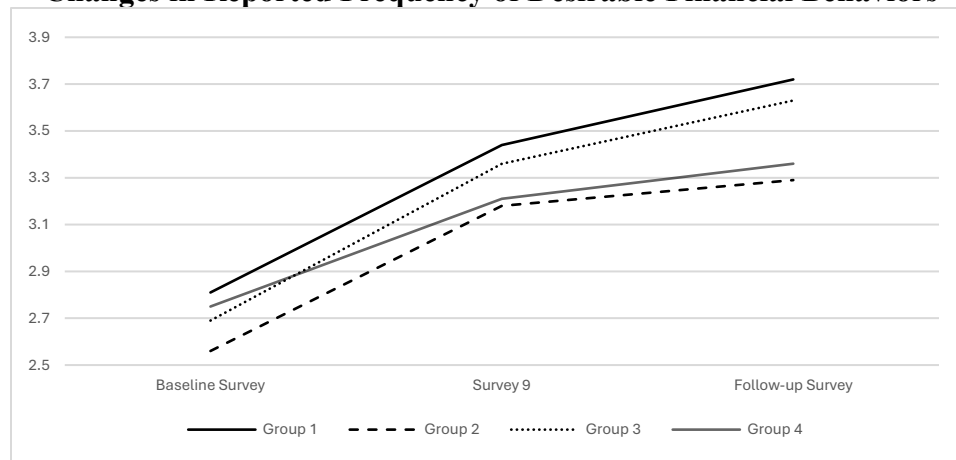
< 0.05), slightly improved six months after they finished the courses, while those in Group 2 and the control group did not significantly change.

Table 6
Post-Hoc Trend Analysis for Financial Behaviors after the Intervention

	Linear Trend	z	p> z	95% CI	
Group 1	0.12	2.03	0.04	0.00	0.2423296
Group 2	0.04	0.62	0.54	-0.08	0.1494399
Group 3	0.12	1.95	0.05	0.00	0.2395664
Group 4	0.05	0.76	0.45	-0.09	0.1938088

However, as the insignificant *group*post* interaction shown in Model 2 indicated, the difference in the changes was not large enough to be statistically significant. Despite the insignificant interaction term, the clearly different trends in Group 1 and Group 3 after Survey 9 in the follow-up period provided preliminary evidence that taking multiple financial education courses could benefit them in the middle or long run. Figure 4 below shows the changes in financial behaviors for each group during the entire course of the study.

Figure 4
Changes in Reported Frequency of Desirable Financial Behaviors



Note: The predicted values were shown in the figure.

Student – Parent Communication on Financial Topics

At the beginning of the study, only 17% of the participants reported that they talked with their parents on financial topics “often” or “very often”. As Model 1 in the table below shows, from the baseline survey to Survey 9, the changes in the frequency of communication were not significantly different across the four condition groups.

Table 7
RMM Estimation Results for Student-Communication Frequency

	Model 1 (baseline – survey 9)	Model 2 (survey 9 - follow-up survey)
Group (Group 4 as the reference group)		
<i>Group 1</i>	0.11	0.26
<i>Group 2</i>	-0.16	-0.04
<i>Group 3</i>	0.03	0.14
Post (reference group = baseline survey in Model 1, = survey 9 in Model 2)	0.05	-0.24*
Group*Post joint test	$\lambda^2 = 1.06, p > 0.05$	$\lambda^2 = 8.03, p < 0.05$
Household income	-0.01	0.03
Married	-0.14	-0.28*
Grade	0.19 *	0.23*
Male	-0.06	-0.01
White	-0.19 *	-0.08
Knowledge_parent	0.001	-0.01
Behavior_parent	0.11	0.09*
Efficacy_parent	-0.001	0.12*
Student interest	0.17 **	0.16**
Constant	1.73 *	1.93 **
Random components		
<i>Std (constant)</i>	0.46 (95% CI: 0.37 – 0.57)	0.62 (95% CI: 0.55 – 0.70)
Wald λ^2	64.82, $p < 0.01$	77.15, $p < 0.01$
LR test vs. linear model	$\lambda^2 = 23.19, p < 0.01$	$\lambda^2 = 120.99, p < 0.01$
ICC	0.30	0.63

*Note: * $p < 0.05$, ** $p < 0.01$. Student demographics, the annual income of the households and parents' financial knowledge, attitudes and behaviors were added in the model as covariates. Based on both AIC and BIC, models without random time effect have better goodness of fit. Therefore, the models only allow the intercepts to vary for individuals.*

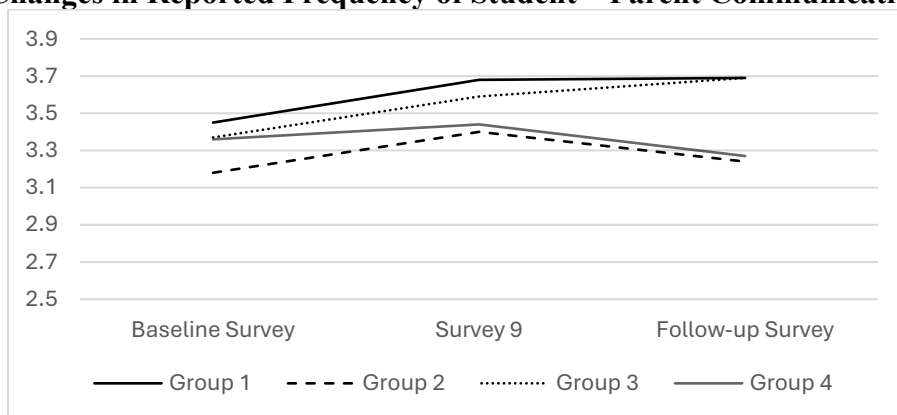
Notwithstanding what the insignificant interaction term suggested, the trend analysis (see Table 8 below) showed that by the end of the last course, students in Group 1 ($\beta = 0.13, p < 0.05$) and Group 3 ($\beta = 0.14, p < 0.05$) had a small but significant increase in their communication frequency, while those in the control group and Group 2 did not have any significant improvement. Although the difference might not be statistically significant, it did provide preliminary evidence that taking multiple courses might help encourage student-parent communication on financial topics.

Table 8
Post-Hoc Trend Analysis for Parent-Student Communications (Baseline- Survey 9)

	Linear Trend	z	p> z	95% CI	
Group 1	0.13	2.28	0.02	0.02	0.27
Group 2	0.04	1.38	0.47	-0.02	0.11
Group 3	0.14	2.15	0.03	0.01	0.26
Group 4	0.05	0.68	0.50	-0.10	0.21

The effect of taking multiple courses was more clearly manifested in the follow-up period of the study. As Figure 5 below shows, six months after students took Survey 9, a clear distinction emerged between those who took multiple courses in the study and those who took no course or only one course.

Figure 5
Changes in Reported Frequency of Student – Parent Communication



Note: The predicted values were shown in the figure.

As Table 9 shows, the post-hoc trend analysis confirmed that while the frequency of student-parent communication of Group 1 and Group 3 did not change significantly, those in Group 2 ($\beta = -0.11, p < 0.05$) and Group 4 ($\beta = -0.12, p < 0.05$) both had a significant decrease in how often they talked with their parents about financial topics. This difference suggested that while taking multiple courses might not have a strong, immediate effect on the participants' financial communication with their parents, it could prevent the decline of communication, which was observed among those who took only one course or no courses.

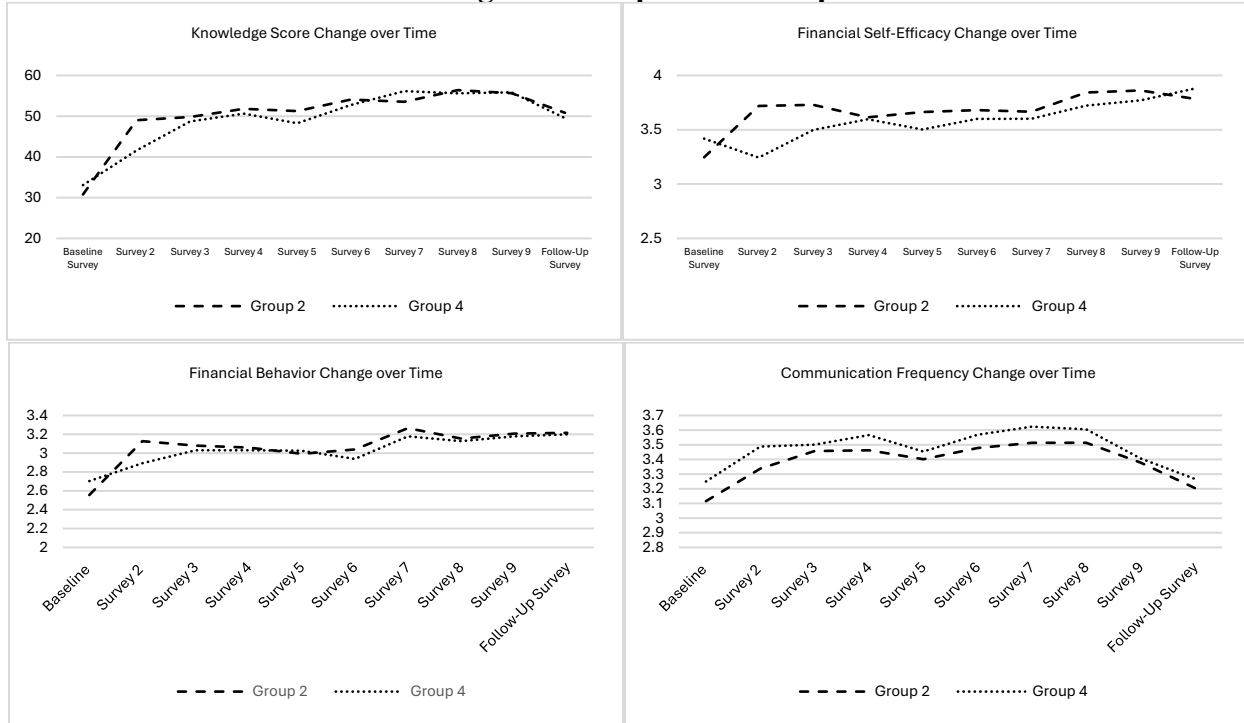
Table 9
Post-Hoc Trend Analysis for Parent-Student Communication after the Intervention

	Linear Trend	z	p > z	95% CI	
Group 1	-0.03	-0.51	0.612	-0.13	0.08
Group 2	-0.11	-2.11	0.035	-0.21	-0.01
Group 3	0.02	0.33	0.743	-0.09	0.12
Group 4	-0.12	-1.97	0.048	-0.25	0.00

Effects of the Introductory Course

As the RMM analyses showed, when the program ended in Spring 2024 (Survey 9), no evidence was found that those who took only one introductory course (Group 2) made larger improvements in any of the outcomes measured than those in the control group did. Nevertheless, this does not mean taking a single introductory course had no effect at all. Due to the long duration of the program, it was necessary to examine if the introductory course had any short-term effects which did not sustain until the end of the program. The figures below show the changes in Group 2 and Group 4 during the study.

Figure 6
Changes in Group 2 and Group 4



Note: The predicted values were shown in the figures. Students in Group 2 took the only course assigned to them between the baseline survey and survey 2.

When all time points were included in the analysis, the RMM estimation and trend tests clearly indicated that even the introductory course alone had a positive impact on the students' financial knowledge, self-efficacy and reported financial behaviors. However, apart from the case of financial self-efficacy, the course only had a short-term impact immediately after students finished the course (Survey 2), and the effect diminished quickly. In the case of financial self-efficacy, two months after students took the introductory course (at Survey 3), although their score did not further increase, they were still significantly more confident than those in the control group. The positive effect ceased to exist over the Summer of 2022 (Survey 4), when no difference was found between Group 2 students and the control group.

Discussion and Conclusion

This study analyzed the effects of a three-year financial education intervention and examined how the effects differed from students who took multiple courses to those who took only one course or no courses. Based on the repeated measure mixed model estimation and post-hoc tests of trend, the study investigated how the financial knowledge, self-efficacy, behaviors and communication changed after students finished the courses and examined if the effects of the courses still existed after the intervention ended. This section summarizes the main findings of the study and discusses the implications for students, educators, and education policymakers.

Consistent with what many studies suggest, our analysis showed that financial education did have a positive impact on students' financial knowledge test scores. However, such positive impacts were only found immediately after students finished those courses and quickly diminished within two months after course completion without additional reinforcement. While the lack of

long-term, sustained effects might be disappointing, the short-term, immediate boost to students' financial knowledge should not be taken lightly. According to the Planned Behavior Theory (Ajzen, 1991), possessing more knowledge on a subject is an important prerequisite to the formation of attitudes toward a behavior, which can eventually lead to behavioral changes. Studies have shown that increasing financial knowledge can make the learners more confident in their financial skills, and increased financial self-efficacy could lead to desirable financial behaviors (Lone & Bhat, 2021). More studies can be done to further analyze how short-term financial knowledge increase might impact long-term attitudes and behaviors differently.

The study also examined the effects of the courses on students' confidence in their basic financial skills. The findings clearly showed the value of taking multiple financial education courses as opposed to only one introductory course. In both situations, students had a significant increase in their financial self-efficacy immediately after the course. However, the effect of a single course was shorter than that achieved by taking multiple courses. The multiple-course model could lead to this positive outcome through several mechanisms. First, as students grew older, they may have started to face more complex and challenging financial situations, for which the introductory course might not be sufficient to help them make informed decisions. By providing more relevant and in-time information and knowledge, the courses on more advanced topics more directly tackled the increasingly complex issues students faced in their daily life, and therefore, more effectively increased their confidence. Second, students who took multiple courses may have had more chances to reinforce what they learned in the past. Through the reinforcement, students were reassured that they were educated on relevant topics so that they could handle real-life situations better.

Based on the students' self-reported frequency of desirable financial behaviors, taking multiple courses did not immediately make a difference. In contrast, the introductory course alone improved students' financial behaviors right after students finished the course. According to the baseline survey, the vast majority of the participants reported not having taken any financial education courses before the study. Therefore, the surge in healthy financial behaviors could be explained by the "newness effect": something perceived as new and different from what people already know may stimulate interest in trying it (Song, 2011). However, this effect did not last long and ceased to exist two months after the course was taken. The lack of lasting effect may provide some critical insights on the timing of financial education and impact evaluation. While receiving financial education as early as middle school can lay a solid foundation for future financial health among students, it may not lead to long-lasting changes in financial behaviors as the students are too young to face real-life financial situations that motivate the formation of any financial habits. As shown by the analysis, though not having an immediate difference initially, those who took multiple courses showed improvement in their financial behaviors six months after the study concluded. Noticeably, the study lasted for about 3.5 years so by the time of the follow-up survey, all participants (who joined the program when they were in the 7th or 8th grade) were in their final years of high school. As the participants transitioned to early adulthood, they may have started to have more real-life situations that required them to act. Only at this point, the advantage of receiving more intensive financial education would have started to manifest, as those who took more courses had more knowledge and skills to support the implementation of desirable financial behaviors.

Although communication with their parents is an important component of adolescents' financial socialization, few studies have analyzed this aspect as a potential effect of financial

education. In line with what the literature on adolescence generally suggests, this study found that teenagers had a strong tendency to refrain from talking with parents. By the last in-study survey, even the participants who took multiple courses only had a small increase in their financial communication with their parents. Nevertheless, an important divergence was observed six months after the intervention. While no further improvement was found among those who took multiple courses, the students who did not take any course or took only one course communicated significantly less often with their parents. This finding lends another piece of evidence to show the value of the multi-course model of financial education: although it might not significantly increase the frequency that adolescents talk with their parents on financial topics, it can help prevent the decline in communication on this important topic during this critical period.

Through the RMM estimation and trend analysis, this study showed the importance of continuous financial education with a series of courses taken over a long period of time. Although the quality of individual courses should not be overlooked, effective financial education that leads to long-term improvement is a journey where students engage in financial learning throughout their development. Therefore, educators and policymakers should, besides focusing on the content design of each program, also pay attention to the synergy of various financial education resources and study the optimal implementation model, such as combining school use and home study time and ideal program intervals, to maximize the values of continuous financial education.

Another significant contribution of the study is that home-based financial education can also lead to significant improvement in key financial capability outcomes. Although a few studies have suggested that home-based financial education could have some unique advantages over school-based programs due to increased parental involvement and more natural and relaxing study settings (Gudmunson & Danes, 2011; LeBaron & Kelley, 2021), there is a lack of empirical evidence to support that. This study fills the gap by clearly showing the positive impact of the courses even though they were taken at home. Moreover, the fact that the courses used in the study were initially designed for school use challenges the assumption that home-based programs must be different from the ones used at school in order to be effective. The findings of the study suggest that well-designed, versatile programs have the potential to benefit both school users and home users. A natural follow-up study would be to compare the learning outcomes of the students who take the courses at home to those who take the courses at school to see in which areas home-based programs underperform and outperform the school-based counterparts.

Limitations

This study has several limitations which should be noted. First, the students in this study were self-selected to participate in the study. Although we did control for their demographics, household socioeconomic conditions and level of interest in participating in the study, it is still possible that the positive learning outcomes were results of the high motivation and dedication of the self-selected participants. Second, although the study used a control group to control the potential bias caused by the natural change students experienced as they grew up, it cannot completely rule out the possibility that the effects detected are caused by the participants' awareness that they were in a research study on financial literacy. To ensure it was indeed the education that caused the positive changes, a natural experiment is needed where the change trajectories of students who took financial education courses in a natural setting are evaluated against a comparable group of students who did not take any course. Last, the participants of the study were given the freedom to take the courses at their own pace at home in each course window without the supervision of the

researchers. Although this arrangement provided a natural, anxiety-free learning environment for the students, the courses might not be used in the optimal way, which could have led to even better learning outcomes. Such an arrangement also made it impossible to examine the potential impact of learner behaviors, such as pace of learning, interval between usage, timing of studying, etc., on the learning outcomes.

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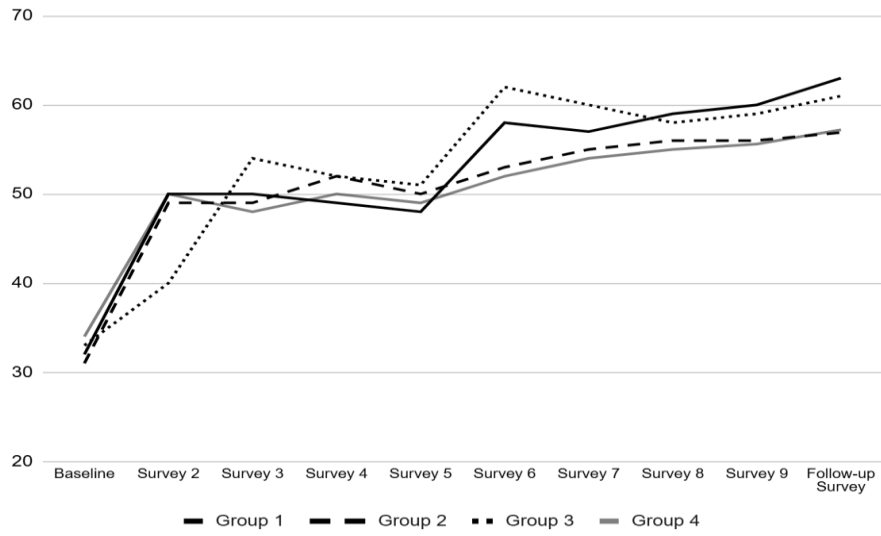
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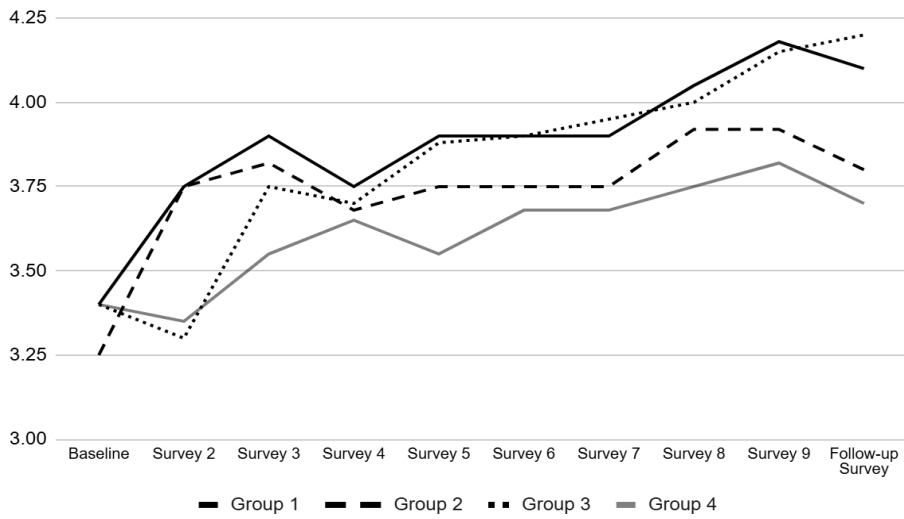
Appendix

Learning Outcomes for Each Group at Each Survey Period

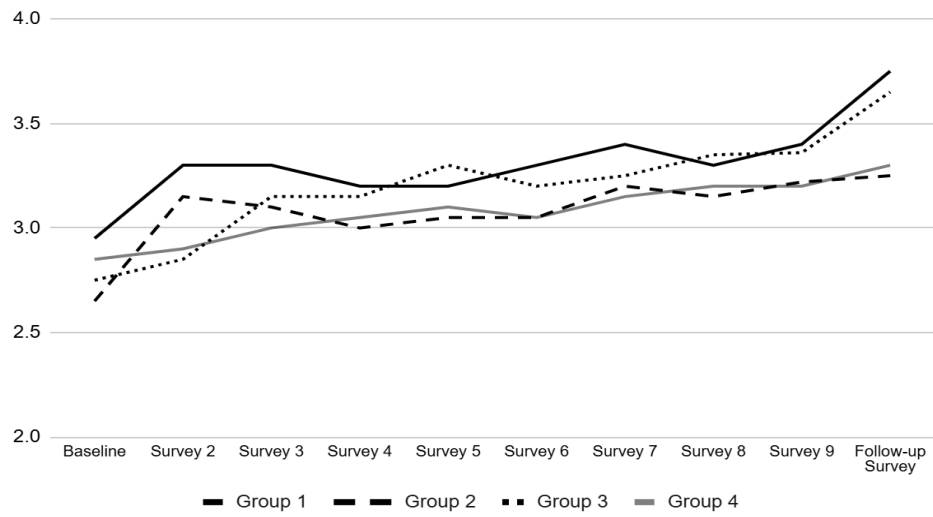
Financial Knowledge



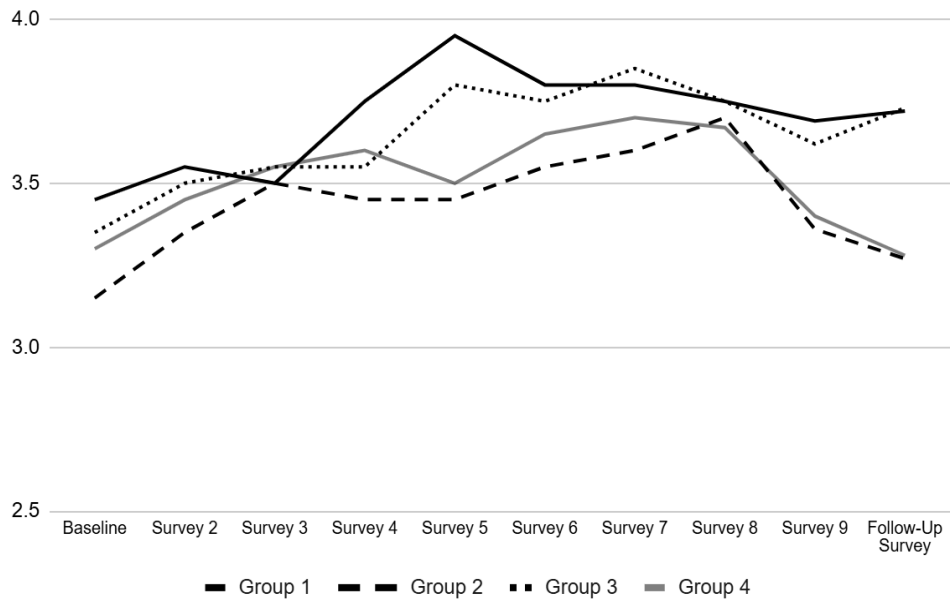
Financial Self-Efficacy



Frequency of Desirable Financial Behaviors



Frequency of Parent-Student Conversations on Financial Topics



Targeted Financial Education: A Pyramid Scheme Education Experiment

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Young adults in the U.S. are reporting larger losses to financial fraud than in the past, and the types of fraud that target young people often vary from those aimed at middle-aged and older individuals. Prior research also indicates that individuals may be more vulnerable to some types of fraud than others and that financial literacy education, aimed at broad protection and knowledge, may not reduce vulnerability to specific forms of fraud. This research uses an RCT experiment to test the efficacy of targeted financial education aimed at protecting students from pyramid scheme fraud, one of the top forms of financial fraud experienced by young adults. We apply three different educational treatments and measure immediate changes to subject knowledge relative to a control group who receives no education. All 183 subjects are undergraduate first-year students at a liberal arts university. Treatments are designed to be scalable, as they include short videos and do not include interpersonal interaction. We also use 6-month and 2-year lagged surveys to measure knowledge retention and behavioral differences across groups. Results inform future educational efforts aimed at reducing consumer vulnerability to pyramid scheme fraud and may inform other targeted financial education interventions.

Keywords: Financial education, experiment, fraud, pyramid scheme

Introduction

“In 2004, a nutrition company offered a life-changing opportunity to earn a full-time income for part-time work. There were only two steps to get started: purchase a \$500 kit and recruit two more members. By 2013, the company was making \$200 million. There was just one problem -- the vast majority of members earned less than they paid in.”

From How to spot a pyramid scheme – TED-Ed Lesson (2019)

Consumers reported losing more than \$5.8 billion to fraud in the U.S. in 2021, representing an increase of more than 70 percent over the previous year (Federal Trade Commission, 2021a). Of

the 2.8 million consumer complaints filed in that year, business and job opportunity fraud – a category which includes pyramid scheme fraud – was among the top five fraud categories. Pyramid schemes impact some age cohorts more than others. Data from 2017 to 2019 revealed that consumers aged 20-39 were 90 percent more likely to report a loss from pyramid scheme fraud than those aged 40 or older (Fletcher, 2019). Pyramid schemes appear in many forms: e.g., as a multilevel marketing (MLM) business opportunity, a gifting scheme, a community lending circle (i.e., sou sou) or chain letter (Bosley et al., 2019; Fair, 2021). At their core, all pyramid scheme offers are built on a pay-and-recruit structure that dooms the vast majority of participants to financial loss (Gastwirth, 1977; Gastwirth & Bhattacharya, 1984). As consumer harm is both inevitable and widespread in pyramid scheme fraud, pyramid schemes are inherently deceptive and are illegal at the state and federal level (e.g., California Attorney General, 2022; Federal Trade Commission, 2021b), both in the United States and in many countries around the world.

Legal cases and media reports highlight the impact of pyramid scheme fraud on young adults. In 2015, the Federal Trade Commission sued Vemma Nutrition Company, alleging that it promoted a pyramid scheme disguised as an energy drink selling multi-level marketing firm and that it promoted its illegal scheme to high school and college students (Federal Trade Commission, 2015). The company promoted its scheme as a superior alternative to higher education and traditional employment but left most of its participants with financial losses (Anglen & Hunt, 2015; Federal Trade Commission, 2016). More recently, law enforcement officials and journalists have warned of pyramid schemes pitches on social media sites favored by young adults, including Instagram and Snapchat, in the U.S. and around the world (BBC, 2019; Martineau, 2018; Mustoe, 2021; Office of the Attorney General of Georgia, 2021).

Research suggests that consumer vulnerability to pyramid schemes is associated with personal characteristics (e.g., impulsivity and low cognitive skills as in Bosley et al., 2019) and place-based factors (e.g., county-level unemployment or low social capital, as in Greenman et al., 2023). Consumer vulnerability is exacerbated by simple lack of knowledge about pyramid scheme fraud. In a lab-in-the-field experiment at the Minnesota State Fair, Bosley et al. (2019) found that approximately half of the 452 subjects thought that an explicit pyramid scheme was a legal offer.

Given the legal attention paid to pyramid scheme promotion, mentioned above, the college setting may be an ideal point for intervention aimed at increasing consumer awareness and reducing vulnerability related to pyramid scheme fraud, specifically, and risky financial decisions, in general. To our knowledge, there is no research studying undergraduate students' knowledge of or ability to recognize pyramid scheme fraud. However, Pena-Shaff et al. (2020) discuss the need to test the efficacy of targeted financial education, especially within vulnerable populations, given the increasing complexity of financial instruments and markets and the growth of predatory practices. Lyons (2004) points to the importance of this education on college campuses and cites survey results that financially at-risk students are particularly open to receiving information that increases their financial literacy. Popovich et al. (2020) note the importance of low-cost financial education for specific student sub-populations, especially those most likely to have higher financial challenges during and after college. Geddes and Steen (2016) argue that the college years are an optimal time to provide financial education as students are often resource-constrained and cognitively able to incorporate course information into their decision making. LaBorde and Mottner (2018) find that financial literacy curricula may be effective in both online and in-person modes of instruction.

Fernandes et al. (2014) caution that studies showing significant positive impacts of financial education likely overstate effects as knowledge and impact are likely to decay over time. Like

Geddes and Steen (2016) and Pena-Shaff et al. (2020), the authors emphasize the importance of “just-in-time” education that can be immediately applied to the actual decisions individuals often face. General principles and “soft skills” used in financial decision making may be more readily retained than objective financial facts, especially when they are reinforced through opportunities for real life application (Fernandes et al., 2014; Hadar et al., 2013). As promoters of pyramid schemes target college students, education on campuses could potentially reduce vulnerability to financial fraud. Application of newly gained knowledge to real-life examples may help to improve learning and reduce subsequent risky behaviors. Furthermore, online education, if effective, might offer low-cost, flexible education that can be introduced or repeated when needed.

In this study, we use an experimental approach to test the efficacy of targeted education for young adults, where that education is explicitly aimed at improving knowledge of pyramid scheme fraud and related consumer harm. We test three different education treatments on 183 first-year college students at a small, liberal arts university. All three treatment groups of students were shown a short, educational (TED-Ed) video entitled “How to spot a pyramid scheme.” For the first group, this was the only informational material. The second group, the self-generated persuasion group, was also shown a short video of a pitch for a now-defunct pyramid scheme. They were then asked to identify, in writing, components of the pitch video that stood out as typical of pyramid scheme recruitment and generate phrases or scripts they could use to persuade a friend from joining the scheme. Finally, the third group, the satirical persuasion group, was shown a short video clip from a popular news-comedy show on HBO discussing pyramid scheme fraud. The treatments are described in more detail in the methodology section. Treatments were designed to be low-cost and scalable. Results indicate that treatment does significantly increase knowledge of pyramid scheme fraud, though knowledge retention and behavioral change may require repetition and “just in time” interventions.

Literature Review

This research draws on the elaboration likelihood model (ELM), combined with other relevant persuasion literature, to inform the treatments and hypotheses. The ELM model suggests that persuasion is impacted by the likelihood and degree to which the delivered message inspires intellectual elaboration (O’Keefe, 2013). Elaboration occurs when an individual considers and potentially integrates received information into their own beliefs. The model suggests two primary routes for persuasion, central and peripheral, with implications for persistence and attitudinal and behavioral changes (Petty & Cacciopo, 1984, 1986). The central route relies on a relatively high level of elaboration and is characterized by thoughtful consideration of the message. Alternatively, the peripheral route is typified by relatively shallow thought giving rise to opinion formation (O’Keefe, 2013).

A variety of source factors work to determine which persuasion process is activated in an individual and the levels and forms of elaboration. Petty and Cacciopo (1984) emphasize the varying importance of source factors with respect to level of processing and persuasion. O’Keefe (2013) and Petty and Wegener (1999) point to the importance of elaboration motivation in determining whether the receiver thinks carefully about the potentially persuasive message. This motivation is often closely related to personal relevance.

The ELM model directly relates to the literature on self-generated persuasion and satire. Both the self-generated persuasion and satirical persuasion literature suggest that these methods are more effective than external persuasion i.e., persuasion from an outside source. Literature suggests

that individuals using self-generated persuasion may experience lower levels of reactance, i.e., they will experience fewer emotions that create resistance to persuasion (Brehm, 1966; Müller et al., 2009). Lower levels of reactance are also more likely to contribute to an individual's ability to engage in careful, issue-related thought, allowing for the central route to persuasion (Petty & Cacciopo, 1984). Additionally, literature suggests that self-generated persuasion may be more creative and convincing as it addresses a particular individual's concerns and avoids perceived restrictions on freedom (Baldwin et al. 2013; Briñol et al., 2012; Greenwald & Albert, 1968; Slamecka & Graf, 1978), suggesting more internal elaboration and thus the central elaboration route. Finally, research suggests that people may be less likely to critically evaluate internally generated information; i.e., individuals are less likely to recognize and correct for internal information (e.g., Mussweiler & Neumann, 2000; Wilson & Brekke, 1994). Satire has a similar, but potentially more peripheral, impact on persuasion. By evoking positive emotions, satire can disarm people, leading to increased perceived credibility and reduced reactance (Burgers & Brugman, 2022; Hendriks & Strick, 2020) while not requiring deeper elaboration. The expectation is for satirical and self-generated persuasion to be more effective than external persuasion in terms of changes in knowledge, attitudes and behavior. Nevertheless, external persuasion is likely to generate more changes in the target audience than no persuasive message at all.

Our study examines the effectiveness of three different persuasion methods, one of which likely triggers individual elaboration typical of the central route while the other methods engage elaboration more closely associated with the peripheral route. All treatments included external persuasion in the form of the video lesson on pyramid scheme fraud and advice on rejection strategies for pyramid scheme offers. Treatment 1 included no additional persuasion content. Treatment 2 added a self-generated persuasion exercise, which presented students with a hypothetical but personally relevant scenario in which they were asked to use the new information to create original language discouraging a friend from joining a pyramid scheme. With this motivation, the central route to judgment was likely activated. Contrast this motivation with Treatment 3 in which students watched a satirical video delivered by a well-known celebrity host on a popular television program. The processing of this message was likely to engage lower levels of elaboration that rely on more superficial “extrinsic features” such as credibility and likeability of the show's host (O'Keefe, 2013). The control group received no persuasion message(s).

Our study captures knowledge at the time of the initial study (i.e., after engagement with persuasion content, for those in treatment groups, and without persuasion content, for those in the control group). We also capture knowledge and behavioral outcomes after 6 months and again after 2 years from the initial study. Regarding longitudinal impacts of persuasion, Petty and Wegener (1999) suggest that when attitudes are shaped through the central route, there is more likely to be an enduring change in knowledge or beliefs that is less susceptible to reversal, where that change is also more closely associated with behavior. Again, this is contrasted with attitude shifts achieved through the peripheral route which tend to be temporary and less predictive of behavior (Petty & Wegener, 1999). As a result, we expect that subjects engaged in self-generated persuasion will be more likely to retain knowledge and report behavioral impacts.

Based on previous literature we retain the following hypotheses:

H1: External persuasion will generate an increase in pyramid scheme knowledge and behavior change at all time periods for measured outcomes.

H2: External persuasion with self-generated persuasion will generate greater increases in pyramid scheme knowledge and behavior change compared to all other conditions (i.e., no

persuasion, external only persuasion, or external with satirical persuasion) at all time periods for measured outcomes.

H3: External persuasion with satirical persuasion will generate greater increases in pyramid scheme knowledge and behavior change compared to no persuasion or external persuasion alone, at all time periods for measured outcomes.

Methodology

To study the efficacy of consumer education, we created three educational treatments. All treatments utilized a TED-Ed video: “How to spot a pyramid scheme” (TED-Ed, 2019). This 5-minute video describes the case of *FTC vs. Vemma Nutrition*, the ways that pyramid schemes are promoted to consumers, the pay-and-recruit structure of a pyramid, and the harm to consumers and society at large. The video was accompanied by potential rejection strategies that could be employed if one was approached with a pyramid scheme offer. All treatment group subjects received written advice, placed after the TED-Ed video, on how to reject a fraudulent offer, including “hard” rejections (e.g., “This sounds like an illegal pyramid scheme. I don't want to get in trouble, and I don't want you to either”) and “soft” rejections (e.g., “Sorry, I'm not really interested in what this business has to offer” or “I don't have the time to join something like that”).






Beyond this TED-Ed video and rejection strategies (i.e., external persuasion), we test the potential impact of self-generated persuasion and satirical persuasion. Treatment 1 received external persuasion only. Treatment 2 received the external persuasion and a self-generated persuasion video and related exercise, described below. Treatment 3 received external persuasion and a satirical persuasion video, also described below. These treatments are summarized in Table 1. The control group received no persuasion materials of any kind.

As summarized above, Treatment 2 subjects were exposed to external persuasion *and* a self-generated persuasion exercise. In the context of fraud, self-generated persuasion is the concept of having the target of a fraud-related communication “persuade him- or herself as to the merits of a given course of action,” namely fraud rejection (AARP Foundation, 2003, B-10). Prior research has established that self-generated persuasion can occur through role playing but can also be accomplished through writing tasks (Loman et al., 2018). In the AARP Foundation study on telemarketing fraud, the researchers employed self-generated persuasion by “asking participants to come up with their own arguments for why they should hang up on fraud criminals, their own ideas for identifying fraud crimes, and their advice to others on dealing with telemarketing fraud” (B-10). Of the multiple “influence” techniques the researchers employed, they found that the self-generated persuasion technique was the only one that decreased response rates to fraudulent offers. To create a self-generated persuasion component in this study, we showed Treatment 2 subjects a short video segment of an actual fraud pitch (Vemma Mesa, 2013): a video of a high-level Vemma Nutrition promoter (i.e., a pitch for the same scheme discussed in the TED-Ed video). After the pitch video, we asked subjects to identify and write warning signs they saw in the pitch. We further asked them to write what they would say to a friend who attended that pitch if they were trying to convince the friend not to join the scheme. Again, this self-generated persuasion exercise occurred after the subjects were exposed to the external persuasion content (i.e., TED-Ed video and rejection strategies) so served as a complement to external persuasion.

For Treatment 3, we added satirical persuasion as a complement to the external persuasion content. In contrast to self-generated persuasion where subject judgment or behavior might be altered by actively convincing him/her own self of some course of action, satirical persuasion tends

to come from an external source. By design, satirical persuasion is a blend of entertainment, information, and opinion (Burgers & Brugman, 2022). While research is mixed on the impact of satire, Burgers and Brugman (2022) found that persuasion effects were stronger for some groups, including young adults. To create a satirical persuasion component, we showed Treatment 3 subjects a short video clip from HBO’s Last Week Tonight with John Oliver, after they were exposed to the external persuasion content. In the satirical video, Mr. Oliver discusses Vemma Nutrition and pyramid scheme fraud (HBO, 2016).

Table 1
Experiment Groups

Control	Treatment 1	Treatment 2	Treatment 3
No educational materials	TED-Ed Video: How to spot a pyramid scheme 	TED-Ed Video: How to spot a pyramid scheme 	TED-Ed Video: How to spot a pyramid scheme 
	No additional content	Actual pitch video (self-generated persuasion) 	HBO Last Week Tonight video (satirical persuasion) 

All subjects responded to the set of pyramid scheme knowledge questions, summarized in Table 2. One of the knowledge questions asked subjects to look at five offers and select all that indicated warning signs of a pyramid scheme. Figure 1 shows an example of an offer that was designed to include such warning signs. Offers included actual pyramid offers, drawn from media or law enforcement reports, and the offer represented in Figure 1 was an actual promotion from Vemma Nutrition. All questions and accompanying images (i.e., offers) are included in the online appendix.

In addition to the pyramid scheme knowledge questions, respondents answered questions about basic demographic characteristics, religiosity (a common risk factor in prior fraud studies, as discussed in Bosley & Knorr, 2018), and prior experiences with pyramid schemes. To measure subject impulsivity (another risk factor identified in prior research, see Deevy et al., 2012), we followed Knutson and Samanez-Larkin (2014) and included the non-planning questions from the Barratt Impulsiveness Scale, a commonly used instrument to measure impulsivity (Patton et al., 1995). We also captured subjects’ financial literacy using questions from Lusardi and Mitchell (2008) and numeracy using questions from Banks and Oldfield (2007). Last, subjects answered questions from the Financial Skill Scale, created by the Consumer Financial Protection Bureau (CFPB). As a complement to financial literacy measures, the Financial Skill Scale was created to capture an “action component—the skills to put financial knowledge to use” (CFPB, 2018, 2).

We invited all incoming first-year students at our university to participate in the experiment (invitations were sent by email to those enrolling in Fall 2019 and Fall 2020). We randomly assigned students to experiment groups by randomly allocating one-fourth of each class to each of the four experiment groups. Subjects were paid \$5 for completion at Time 1. A gift card drawing was also used as an incentive for Time 2 and Time 3 survey participation. 183 students participated in the initial study (Time 1), and the breakdown of participants by experiment group is presented in Table 3. For context, the university had approximately 1,000 first-year students during this time, so 18.3 percent of first-year students participated in the study. Of those assigned to the control group, more subjects participated. While subjects did not know their group assignment, we expect that more control group subjects completed the survey due to the shorter duration (i.e., no video content). At the time of initial participation (i.e., Time 1), subjects were told that they would receive a 5-minute follow-up survey in six months (Time 2) and again in two years (Time 3). Table 3 also reports the number of students who responded to the lagged surveys, by experiment group. Lagged surveys had the same pyramid knowledge questions as the original survey instrument, though question and answer order differed.

Table 2
Pyramid Scheme Knowledge Questions

Question	Question Language	Correct Answer
Difference from Ponzi	What is one identifiable way that a pyramid scheme is different from a Ponzi scheme?	Participants make money from recruiting other participants.
Illegal	Pyramid schemes are illegal.	True.
Pay & Recruit	What are you typically asked to do when you join a pyramid scheme?	All the above. [Pay money. Recruit new sellers/promoters. Teach your recruits to do (a) and (b).]
Outcome	In a pyramid scheme which of the following is true?	The vast majority earn less than they pay in.
Levels	In a pyramid scheme where each participant recruits six new people, recruitment would exceed the world's population by the _____ level.	13 th
Presentation	Pyramid schemes can be presented as:	All of the above [Gifting groups, Investment clubs, Multilevel marketing business opportunities]
Pyramid Offers Identified	While all of the offers below may look suspicious, please review the images and look for those that show specific warning signs of a pyramid scheme. Identify the offer(s) above that show specific signs of pyramid scheme fraud?	Options A, C, and D (shown in the online appendix) had warning signs of pyramid scheme fraud

Figure 1
Offer with Pyramid Scheme Warning Signs

The 2&Go Program

Step 1: Buy an Affiliate Pack to get you started.

Step 2: Get on Auto-delivery to get your monthly supply of products and stay bonus qualified!

Step 3: Find 2 people who feel like you do, who want time and financial freedom. Teach them to follow the 2&Go program!

Table 3
Sample Size by Experiment Group and Timing

	Total	Control	Treatment 1	Treatment 2	Treatment 3
Time 1	183	60	45	35	43
Time 2	106	30	31	19	26
Time 3	80	24	21	18	17

Data and Analysis

Descriptive Statistics

Table 4 provides subject characteristics by experiment group for responses in Time 1. In general, the students who participated in the study were more likely to be White and female than our student demographics would have predicted, as the first-year class in both years was approximately two-thirds female and just over one-half White students. White, female students were especially overrepresented in Treatment 3. There are also some differences in past experiences between experiment groups, with over 73 percent of Control, Treatment 1 and Treatment 3 participants reporting that they knew someone else who had been recruited by a pyramid scheme in the past while only 57 percent in Treatment 2 reported that prior experience. Note that over half of subjects in every experiment group reported being recruited for a pyramid scheme at some time in the past.

Table 4
Mean Characteristics by Experiment Group – Time 1

	Control	Treatment 1	Treatment 2	Treatment 3
Demographics/Experiences				
Female	0.7167	0.7556	0.7429	0.8372
Age	18.3	18.3	18.4	18.4
White	0.7500	0.7556	0.7429	0.8372
Religiosity	2.0500 (of 4)	2.1560 (of 4)	2.1710 (of 4)	2.1630 (of 4)
Recruited in Past -Others	0.8167	0.7333	0.5714	0.8140
Recruited in Past -Self	0.5833	0.5778	0.5429	0.5116
Other Knowledge/Attributes				
Impulsivity	23.47 (of 44)	22.80 (of 44)	21.57 (of 44)	21.70 (of 44)
Numerosity	1.9670 (of 3)	2.2222 (of 3)	1.9710 (of 3)	2.2090 (of 3)
Financial Literacy	1.9333 (of 3)	2.0670 (of 3)	1.9710 (of 3)	1.9300 (of 3)
Financial Skill	23.0500 (of 40)	23.2200 (of 40)	24.0300 (of 40)	23.0700 (of 40)

Figure 2 shows the proportion of correct responses by experiment group. Before controlling for covariates, it appears that treatment did increase scores on nearly every question, where the largest change was in the “Illegal” question. Note that the control group response on this question aligned with the Bosley et al. (2019) finding, as just over half of control group respondents reported that pyramid schemes are illegal. In contrast, nearly all subjects in the treatment groups reported that pyramid schemes are illegal in the United States. The regression results section reports estimated average treatment effects and correlates of pyramid scheme knowledge.

We measure the total number of correct answers as the sum of correct responses to six questions represented in Figure 2 plus a point for each correctly identified pyramid scheme offer, for a total possible score of nine. While sample sizes are diminished in the six-month (Time 2) and two-year (Time 3) surveys, we use the lagged survey data to analyze knowledge retention and potential behavioral differences. Our full sample retention is 58% at 6 months and 44% at 2 years. Although the final sample size is small, the retention is in line with other longitudinal studies with samples of emerging adults (Hanna et al., 2014). We asked the same pyramid scheme knowledge questions (though with changes to question and answer order) at Times 1, 2 and 3, and we asked new questions about student experiences since the initial survey in Time 2 and 3. Specifically, we asked if they have been recruited for a pyramid scheme (and, if so, how they responded), if they have sought out additional education, and if they have talked with a friend or family member about this form of fraud. We were careful not to require or pressure a subject to respond that they had taken an illegal action (i.e., joining a pyramid scheme) so the options students could choose were essentially different forms of rejection or “other.” We do not explicitly discuss or analyze subject response to pyramid scheme offers, as all subjects who reported a pyramid scheme exposure between Time 1 and Time 3 indicated that they did not participate in the pyramid scheme.

Figure 2
Pyramid Scheme Knowledge Questions at Time 1 – Share of Correct Responses

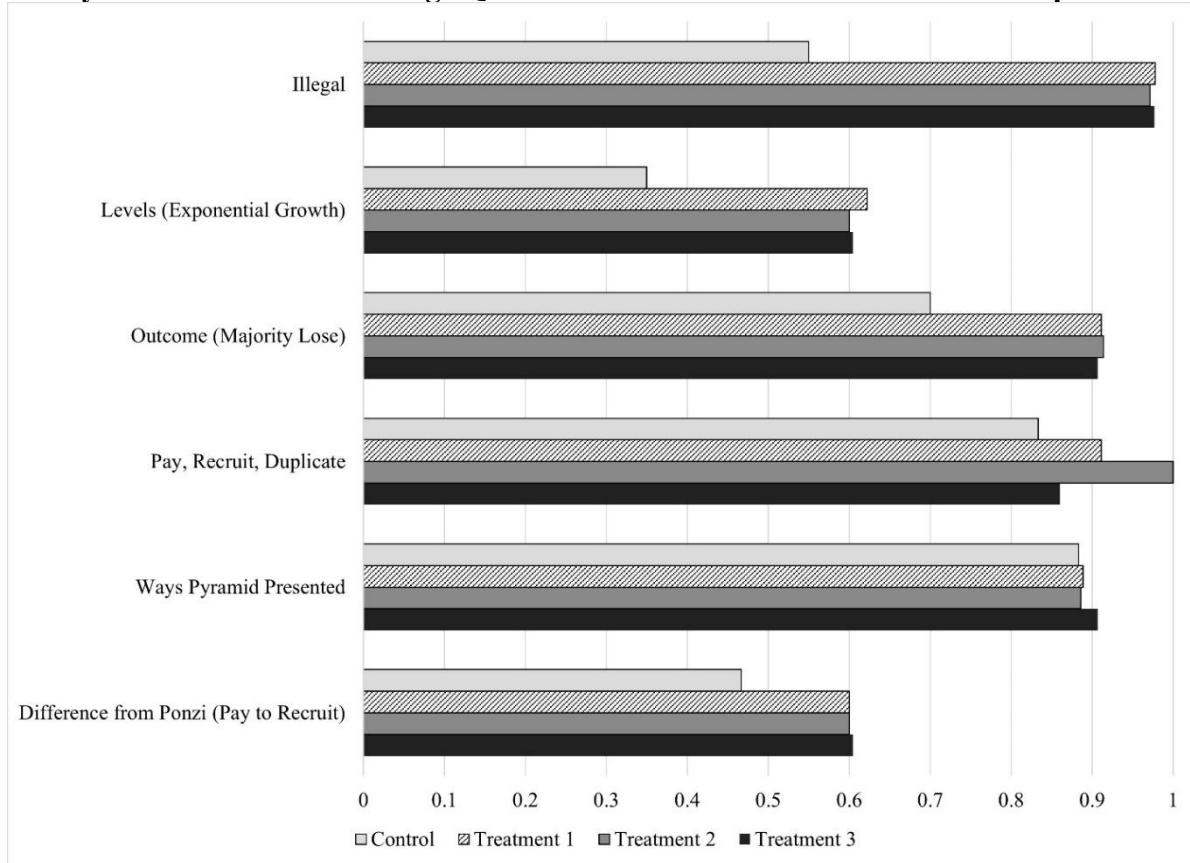


Table 5 reports the average values by experiment group for key outcome variables. There are some differences in respondents at the six-month and two-year mark: 64 respondents answered both the six-month and two-year surveys; 44 responded to the six-month but not the two-year survey; and 16 responded to the two-year but not the six-month survey. On the question of whether pyramid schemes are illegal, the share of correct responses did remain higher for treated subjects than for those in the control over time, and Treatment 2 subjects (those with the self-generated persuasion exercise) seemed to retain this knowledge more than other groups.

On self-education and peer-education, the average values do not indicate that treated subjects engaged more in these activities than the control group. It is important to note that the very act of answering the pyramid knowledge questions likely provided some education to the control group subjects, even though they did not see the TED-Ed video or experience a persuasion element. This may explain the finding that the control group was more likely than others to say that they educated a peer over the two-year period of our study, that one-third sought out additional education on their own, and that the percent that understood it was illegal increased from Time 1 to Time 3. It is also possible that other experiences and information are responsible for this change in knowledge over time, or that the students who responded to our questions over time had higher levels of knowledge than those who did not.

Table 5
Means by Experiment Group and Question

	Control	Treatment 1	Treatment 2	Treatment 3
	Time 1			
Total Number Correct (of 9 possible)	6.4670	8.2440	8.1710	7.9770
Illegal (share responded yes)	0.5500	0.9778	0.9714	0.9767
Pyramid Offers Identified (of 3 possible)	1.8830	2.4220	2.2290	2.1400
	Time 2 (six months)			
Total Number Correct (of 9 possible)	7.2000	8.0000	7.7370	7.8850
Illegal (share responded yes)	0.5333	0.7097	0.8421	0.8077
Pyramid Offers Identified (of 3 possible)	2.3670	2.3550	2.1580	2.3080
Recruited Since Time 1 (share responded yes)	0.3000	0.3226	0.2105	0.4615
Self-Educated Since Time 1 (share responded yes)	0.3333	0.3226	0.2632	0.1923
Peer-Educated Since Time 1 (share responded yes)	0.5333	0.3871	0.1579	0.3846
	Time 3 (2 years)			
Total Number Correct (of 9 possible)	6.5000	7.0048	7.1670	7.0590
Illegal (share responded yes)	0.6250	0.7143	0.8889	0.7059
Pyramid Offers Identified (of 3 possible)	2.2080	2.3810	2.3890	2.4710
Recruited Since Time 1 (share responded yes)	0.5000	0.3333	0.3333	0.5294
Self-Educated Since Time 1 (share responded yes)	0.3333	0.4286	0.2778	0.3529
Peer-Educated Since Time 1 (share responded yes)	0.5000	0.3333	0.3333	0.4706

To assess differences in Time 2 and Time 3 respondents, relative to non-respondents, we test for statistical differences in average characteristics. Among demographic characteristics, we find that White students were more likely to respond to our Time 2 and Time 3 questions than non-White students (difference significant at the 1% level). Regarding non-demographic characteristics, we find that students with higher financial literacy and numeracy scores at Time 1 were somewhat more likely to respond in Time 3 (difference significant at the 10% level) but were no more or less likely to respond in Time 2. Finally, we find that students with a higher Total Number Correct in Time 1 were more likely to respond in Time 2 (significant at the 1% level) and in Time 3 (significant at the 5% level). There is no indication that this non-response bias differs between experiment groups, and we discuss implications of these differences when discussing correlates below.

Regression Results

We estimate average treatment effects for multiple outcome variables that capture pyramid scheme knowledge. Specifically, we consider the following outcome variables: the overall “Number Correct” on the pyramid scheme knowledge questions (varies from 0 to 9), the “Illegal”

yes/no question, and the “Pyramid Offers Identified” (varies from 0 to 3 based on the number of pyramid scheme offers correctly identified). For the binary “Illegal” outcome variable, we estimate a linear probability model. Identification of the treatment's causal effect on the outcome variable is achieved through the experimental design and the randomization of treatment assignment. Beyond analysis of average treatment effects, we explore the correlates of these outcome variables. Table 6 reports the regression results.

Average treatment effects in Time 1 are positive and statistically significant, generally at the 1% level. For example, the total number of correct answers rose, on average, by nearly 2 for those in Treatments 1 and 2, and by closer to 1 point for those in Treatment 3 (all else equal), as shown in Column 1 of Table 6. While the three treatments were, on average, quite similar in teaching students that pyramid schemes are illegal, Treatments 1 and 2 appeared to have a larger effect on total number correct and the ability to identify pyramid scheme offers than Treatment 3, suggesting that satirical persuasion may not be as helpful for immediate acquisition of financial knowledge as external persuasion alone or external persuasion paired with a self-generated persuasion activity. That said, differences in average treatment effects between treatment groups were generally statistically insignificant. One exception was that, for the number of pyramid scheme offers correctly identified in Time 1, the average treatment effect in Treatment 1 (external persuasion) was greater than in Treatment 3 (external plus satirical persuasion) at the 10% significance level, with covariates included. Beyond average treatment effects, it appears that prior experience (i.e., having personal experience with prior pyramid scheme recruitment, either oneself or through a friend or family member) is positively associated with total score and with the number of pyramid scheme offers correctly identified. As in prior fraud studies, impulsivity is negatively associated with pyramid scheme knowledge, though this relationship is only statistically significant for the total score variable at the 5% level. White respondents also had a higher total score in Time 1, on average, all else equal.

Time 2 results indicate that overall pyramid scheme knowledge after six months may be higher for those with treatment, though average treatment effects and statistical significance have weakened with the passage of time (and, likely, with the reduction in sample size). On the specific question of whether pyramid schemes are illegal, it is interesting to note that average treatment effects for Treatments 2 and 3 (external persuasion, combined with self-generated or satirical persuasion) are statistically significant while they are not for Treatment 1 (external persuasion only), albeit only significant at the 10% level. Time 3 results reflect the effects two years after treatment. While nearly all treatment effect estimates are positive, the magnitude of the estimates has fallen relative to Time 1 and 2 and none are statistically significant with covariates included.

In line with prior research, impulsivity – measured at Time 1 – appears to be a risk factor for students as it was negatively related to total score and knowledge of illegality in Time 3 (significant at the 5% level). Additionally, financial literacy measured at Time 1 is positively associated with total score and pyramid scheme offer identification in Time 3 (significant at the 5% level), suggesting that pre-college financial education may provide longer term benefits. This finding may be affected by the non-response bias discussed in the prior section, which indicated that students with higher financial literacy were somewhat more likely to respond in Time 3.

While not depicted in Table 6, we did test for statistically significant differences in other outcome variables by experiment group (e.g., having been recruited, having sought out additional education, or having engaged in peer-education since Time 1). The only statistically significant result was a negative relationship between Treatment 2 and engagement in peer-education ($p=0.098$) at Time 2. Overall, we do not have evidence that treatment altered the likelihood of

being recruited (or the ability to recognize that you are being recruited for a pyramid scheme), the propensity to seek out additional education on pyramid scheme fraud, or the propensity to talk to peers about this form of fraud. Our ability to analyze longer-term knowledge and outcomes is hindered by low sample sizes, though there are no changes in these findings even when treatment groups are combined.

Overall, our results indicate support for Hypothesis 1, in part, as external persuasion (included in all treatments) did increase knowledge about pyramid scheme fraud at Time 1, on average. Based on tests of statistical differences between treatment groups, we do not find support for Hypotheses 2 and 3 at Time 1, as those who received external persuasion with self-generated persuasion or satirical persuasion did not have higher knowledge scores, on average, than those with external persuasion alone. Longitudinal results provide limited support for Hypotheses 2 and 3, as there are some weak signals that retention of knowledge in Time 2 and 3 may have been higher for those who received self-generated or satirical persuasion, specifically in their ability to correctly report that pyramid schemes are illegal. Regarding the differential impact of self-generated persuasion relative to satirical persuasion, we find that self-generated persuasion generated larger initial knowledge gains (in Time 1) and, possibly, better retention at the two-year mark (Time 3). We find no support for behavior impacts in this study. We discuss potential reasons in the following section.

Table 6
Regression Results

	Time 1			Time 2			Time 3		
	Number Correct	Illegal	Pyramid Offers Identified	Number Correct	Illegal	Pyramid Offers Identified	Number Correct	Illegal	Pyramid Offers Identified
Treatment 1	1.7306*** (0.2796)	0.4255*** (0.0637)	0.5314*** (0.1515)	0.7750* (0.4371)	0.1322 (0.1174)	0.0181 (0.2109)	0.4983 (0.4599)	0.0996 (0.1349)	0.1333 (0.2482)
Treatment 2	1.7575*** (0.3083)	0.4082*** (0.0703)	0.4157** (0.1670)	0.6378 (0.5200)	0.2568* (0.1397)	-0.1657 (0.2509)	0.4304 (0.4599)	0.2171 (0.1435)	0.2221 (0.2639)
Treatment 3	1.3499*** (0.2882)	0.4105*** (0.0657)	0.2224 (0.1562)	0.6931 (0.4570)	0.2253* (0.1228)	-0.0378 (0.2205)	0.2411 (0.4970)	-0.0015 (0.1458)	0.2357 (0.2683)
Other Recruited	0.4789* (0.2646)	0.0061 (0.0603)	0.3172** (0.1434)	0.0463 (0.3907)	-0.1586 (0.1050)	0.0739 (0.1885)	0.2578 (0.4293)	0.0266 (0.1260)	0.2134 (0.2317)
Self Recruited	0.3866* (0.2283)	-0.0018 (0.0520)	0.3135** (0.1237)	0.0328 (0.3443)	-0.0365 (0.0925)	0.0015 (0.9929)	-0.1756 (0.3742)	-0.0850 (0.1098)	-0.1591 (0.2020)
Female	-0.2354 (0.2584)	-0.0270 (0.0589)	-0.0475 (0.1400)	0.0866 (0.4119)	-0.0305 (0.1107)	-0.0436 (0.1987)	0.4732 (0.4147)	0.1250 (0.1217)	0.1983 (0.2238)
White	0.6770** (0.2698)	-0.0030 (0.0615)	0.0625 (0.1462)	-0.5479 (0.4885)	-0.0879 (0.1312)	-0.2263 (0.2357)	-0.8165 (0.5126)	-0.3036** (0.1504)	-0.1805 (0.2766)
Religiosity	-0.1030 (0.1053)	0.0034 (0.0240)	-0.0531 (0.0571)	-0.1438 (0.1694)	0.0982** (0.0455)	-0.0953 (0.0817)	-0.1227 (0.1729)	-0.0499 (0.0507)	0.0529 (0.0933)
Impulsivity	-0.0688** (0.0303)	-0.0090 (0.0069)	-0.0208 (0.0164)	0.0118 (0.0502)	-0.0079 (0.0135)	-0.0126 (0.0242)	-0.1101** (0.0546)	-0.0364** (0.0160)	0.0190 (0.0294)
Numerosity	0.2035 (0.1261)	0.0136 (0.0287)	0.1106 (0.0683)	0.2587 (0.2009)	-0.0011 (0.0540)	0.0398 (0.0969)	-0.0394 (0.2012)	-0.0292 (0.0590)	-0.0330 (0.1086)
Financial Literacy	0.0985 (0.1230)	-0.0446 (0.0280)	0.0214 (0.0667)	0.1958 (0.1980)	-0.0842 (0.0532)	0.0537 (0.0955)	0.4171** (0.1959)	-0.0507 (0.0575)	0.2558** (0.1057)
Financial Skill	-0.0320 (0.0225)	-0.0004 (0.0051)	-0.0129 (0.0122)	0.0310 (0.0370)	-0.0145 (0.0099)	0.01545 (0.0178)	-0.0348 (0.0388)	-0.0094 (0.0114)	0.0063 (0.0210)
Intercept	7.4839*** (1.2779)	0.8405*** (0.2913)	2.0660*** (0.6924)	5.8951*** (2.0653)	1.2860** (0.5548)	2.4359** (9964)	9.5843*** (2.2586)	2.1323*** (0.6626)	0.9888 (1.2191)
n	183	183	183	106	106	106	80	80	80
R ²	0.3494	0.3093	0.1865	0.0864	0.1873	0.0533	0.1928	0.2143	0.1199
Adjusted R ²	0.3035	0.2605	0.1291	-0.0315	0.08242	-0.0689	0.0482	0.0735	-0.0377

Discussion and Conclusion

The goal of this study was to explore the efficacy of financial education, specifically focused on pyramid scheme fraud. Using an experimental framework, we estimated the causal impact of information treatment (i.e., external persuasion) and complementary persuasive content (i.e., self-generated persuasion and satirical persuasion). We measured short-term knowledge effects, as well as longer term effects on knowledge and behavior. Behavioral outcomes included the individual's identification of and response to pyramid scheme offers, proactive self-education, and peer education. Participants were first-year undergraduate students in a small liberal arts university.

We find that treatment increases student knowledge of pyramid scheme fraud, and that some of those knowledge effects persist for six months. Specifically, subjects with self-generated or satirical persuasion were more likely to remember that pyramid schemes were illegal than those with external persuasion alone. While we do not generally find statistically significant differences in pyramid scheme knowledge after two years, subjects in the treatment groups did have higher recall that pyramid schemes are illegal after two years, especially in Treatment 2 (i.e., the group with external and self-generated persuasion) where 89% of subjects answered this correctly as compared to 62% of subjects in the control group (i.e., those with no persuasion). Prior research has found that effects of education can be temporary, and that self-generated persuasion may generate larger and longer-lasting effects than other forms of persuasion (AARP Foundation, 2003; Baldwin et al., 2013; Müller et al., 2009; Mussweiler & Neumann, 2000). Beyond knowledge effects, there were no significant differences in behavior across experiment groups. While we expected that subjects in treatment groups might be more likely to seek additional information or educate a peer (in line with the Federal Trade Commission's "Pass it On" campaign), we do not observe this difference in the data. In our experiment, control group subjects did respond to questions about pyramid scheme fraud, identical to those answered by treated subjects. It is possible that the questions themselves prompted self or peer education among control group subjects, thereby shrinking differences between the groups, even though these individuals were not exposed to the educational treatment or other forms of persuasion and were not provided with the correct answers to the pyramid scheme questions. It is also possible that behavioral differences would be observed with larger sample sizes, or if subjects responded later in life (i.e., after college). Additionally, our outcome measures may not fully capture the impact of our treatments. Beyond the outcome measures we considered, a longitudinal study could explore the long-term impact of this type of targeted financial education on overall financial well-being (i.e., perceived financial security as described in Lusardi, 2019) or on financial skill (i.e., the capacity to "find, process, and act on information" as described in CFPB, 2018, p. 2).

Our educational intervention was applied one time (i.e., in the first year of college) and periodic "refreshers" may improve knowledge retention and behavioral impact. For example, Burke et al. (2022) found that the gains of an online module aimed at reducing fraud susceptibility persisted when accompanied by follow-up messages (i.e., a short video or text). However, prior research has also shown that the amount of education itself (e.g., the number of lessons) may not be important if the recipient does not have a chance to apply the knowledge in the near term (Lyons et al., 2006). Ideally, refreshers would be aligned with the recipient's life stage and offered in a "just-in-time" fashion (i.e., close to the time when they can make use of the information), and remain focused on the specific behavior the education is intended to help with (Amagir et al., 2018; Fernandes et al., 2014; Geddes & Steen, 2016; Pena-Shaff et al., 2020). Refreshers could be administered through integration in age-tailored financial literacy curricula but could also take the

form of focused communications or social media messages, as in the private sector (Kuchciak & Wiktorowicz, 2021). Content for refreshers could include information about recent fraud cases (e.g., schemes mentioned in the media or in government press releases) or include relevant fraud statistics (e.g., informed by the “Explore Data” tool for the Federal Trade Commission’s Consumer Sentinel Network) to improve salience.

As in most longitudinal studies, non-response and attrition complicated our analysis, lowering efficiency and introducing sources of potential bias (e.g., as discussed in Gray, 2016 and Cumming & Goldstein, 2016). Non-response in our initial survey reflected factors identified in prior literature (i.e., lower response rate among males and non-White students as in Blaney et al. (2019) and Porter & Whitcomb (2005)), limiting generalizability of results to the broader student population. Attrition in our study was affected by multiple factors including, but not limited to, overall university retention rates. Future studies could ask for multiple contact methods, including personal email addresses or phone numbers, to facilitate ongoing contact and communication (Santos & Jones, 2021) and reminders could be sent to respondents and non-respondents (Kapteyn et al., 2006). A detailed plan to anticipate and address non-response and attrition, as suggested by Krenzke et al. (2006), could include reminders that a study period is nearing, and reminders could include discussion of study benefits (Abshire et al., 2017) and/or the negative impact of attrition on study quality (Ritchey et al., 2023).

As discussed above, refreshers could improve knowledge retention and promote behavioral change but could also serve as a form of ongoing communication to maintain salience and engagement in the study over time, increasing retention (Santos & Jones, 2021). Tailored strategies could also be used to strive for higher response rates and retention for subgroups (e.g., males and non-White students) as discussed in recent studies (e.g., Abshire et al., 2017; Gray, 2016; Lynn, 2017). Supplemental incentives, including those that increase over time or that reward a milestone (e.g., a raffle for those that complete all waves) could also be employed to elevate retention (Soprano et al., 2024), while avoiding incentive types that have the potential to exacerbate non-response bias (e.g., incentives based on response speed, as discussed in Blaney et al., 2019). These strategies could help to increase efficiency of estimated treatment effects and generalizability of findings.

Beyond average treatment effects, correlates of pyramid scheme knowledge included prior experience with pyramid scheme fraud, as those with prior exposure had larger initial knowledge gains. This may suggest that the information treatment was more salient for those with prior exposure (Lyons, et al., 2006). Future research could further probe ways to learn from prior experiences to improve consumer protection. For example, victim (or near-victim) stories from similarly aged individuals could be shared as part of the refresher education discussed above. Beyond prior experience, impulsivity was associated with some outcome variables (negatively), in line with prior research on pyramid scheme fraud (Bosley et al., 2019) and prior studies on consumer financial fraud (Deevy et al., 2012; FINRA, 2021; Koning et al., 2024; Knutson & Samanez-Larkin, 2014)). Lastly, initial financial literacy (measured at Time 1) was positively associated with some aspects of pyramid knowledge at the two-year mark, though it is unclear if this is driven by non-response bias.

Informed by correlates, educational curricula could include a “personal risk” quiz that includes financial literacy, impulsivity, and fraud knowledge questions to alert individuals to personal risk factors and proactive countermeasures (e.g., taking extra time to make financial decisions or seeking advice from an outside party). The curricula could also be built to be tailored and adaptive, so that those with lower knowledge, limited prior experience, or higher impulsivity could receive

additional module(s) to address those specific risk factors. This method may also reduce reactance if it is perceived as being directly tailored to the respondents' needs. Alternatively, additional education (e.g., in-person experiential workshops) could be offered to high-risk groups, such as first-generation college students (Annabi et al., 2018), offered in partnership with student groups and/or student affairs staff.

Given budget limitations, an institution may lack the funds or staff to employ highly customized, in-person components and prior studies have demonstrated efficacy of online-only modules in improving financial knowledge (Agasisti et al., 2023) and reducing fraud susceptibility (Burke et al., 2022). As our study provides evidence of short to medium-term knowledge gains via an online-only module, we find that focused education might be helpful as a low-cost consumer protection device for young adults. In contrast to a full course with in-person instruction designed for broad literacy (e.g., high school curriculum described in Asarta et al., 2014), we designed the treatment to be short, focused, and scalable. For example, a college campus could encourage or require students to complete the treatment in 5-10 minutes (5 minutes if only the TED Ed talk and up to 10 minutes with the self-generated persuasion content). Similarly, a religious institution or tight knit community group, often susceptible to pyramid scheme fraud (Greenman et al., 2023), could provide this education to its members without any financial expenditure. It may be useful to add the self-generated persuasion component, especially if this task can be done in writing (within the online module) and without additional cost.

As the video(s) we used were drawn from publicly available sources, the cost of creating the educational intervention materials was limited to subject payments, discussed below, and the time invested by our research team to create the intervention and survey tool. We utilized our institution's existing survey software and the educational materials (i.e., videos and related questions) were embedded in the survey tool so that all eligible subjects received one message that invited them to participate and provided all of the educational material and questions in one embedded link. All but one of the pyramid scheme knowledge questions we utilized were drawn from the publicly available TED-Ed lesson (available under the "Think" section). We created the content for the "identify a pyramid scheme" question using publicly available news articles about fraud cases and, while we wrote the questions related to pyramid scheme identification, self-generated persuasion, and behavior, future adopters could utilize or alter the content and questions provided in our online Appendix.

Creation of additional components (e.g., a "personal risk" quiz, educational reminders such as texts or short videos, in line with Burke et al., 2022, or customized elements) would require an additional front-end investment of staff/faculty time. Once created, implementation time would be largely limited to identification of and communication with eligible participants and data analysis (determined by institutional/program goals), as most survey software can automate data collection and reminders. We do not anticipate significant differences in cost or scalability based on institution type (e.g. community college versus a university) if the targeted educational program is online and relies heavily on survey software with automation and analysis features (e.g., Qualtrics). That said, cost and scalability would vary more by institution type if the program included in-person components or other highly customized features.

Regarding financial incentives, we paid students \$5 each to participate in the initial survey and we held a gift card drawing for those who completed the 6-month and 2-year surveys. Payment would not be needed if the educational unit was included in a compulsory activity or course, or if the goals of the implementers were different than our own (e.g., if the implementers were not themselves interested in capturing data to measure intervention effectiveness, or if implementers

were interested in providing targeted education on a voluntary basis – for instance, to members of a community group). If not embedded in a mandatory course or incentivized with rewards, the educational intervention could suffer from limited participation (and possibly more severe non-response and attrition bias), as with any voluntary survey or educational intervention. As mentioned above, partnerships with student groups and student affairs personnel could increase participation in non-mandatory, uncompensated programs, and salient messages (i.e., new stories of frauds targeting young people and the importance of financial wellbeing and self-efficacy) could increase motivation to complete the educational module.

Further research is needed to identify ways to improve knowledge retention and encourage behavioral and sentiment change, to reduce susceptibility to consumer financial fraud using targeted education. To replicate this experiment with a larger and more diverse sample, researchers could collaborate with other institutions to conduct a multi-site study, one that ideally includes treatment boosters (i.e., refreshers). It is possible that more experiential (and potentially, more costly) treatment would be needed to generate greater levels of inoculation to pyramid schemes or other types of fraud in the long run, especially for high-risk subgroups. Researchers could partner with organizations who share similar educational goals (e.g., the Federal Reserve Bank system, a state or federal regulatory body, a university extension service, or consumer protection group) to support a more intensive educational program.

Overall, we find that a low-cost, targeted financial education program can generate knowledge gains relevant to specific financial decisions. Such programs could be a useful complement to broader financial education initiatives, especially in the context of high-risk judgments and decisions.

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APPENDIX

A.1 Pyramid Scheme Knowledge Questions

What is one identifiable way that a pyramid scheme is different from a Ponzi scheme? *

- A.) Participants pay in money they may not recover.
- B.) Participants are often promised income or returns that are misleading.
- C.) Some people will make money and will often promote "winnings" to others.
- D.) Participants make money from recruiting other participants.

Pyramid schemes are illegal. *

- True
- False

What are you typically asked to do when you join a pyramid scheme? *

- A.) Pay money.
- B.) Recruit new sellers/promoters.
- C.) Teach your recruits to do (a) and (b).
- D.) All of the above.

In a pyramid scheme which of the following is true? *

- A.) The vast majority earn less than they pay in.
- B.) About half earn a profit.
- C.) The vast majority earn a profit.
- D.) No one earns a profit.

In a pyramid scheme where each participant recruits six new people, recruitment would exceed the world's population by the ___ level.

- 6th
- 8th
- 13th
- 20th

Pyramid schemes can be presented as: *

- A.) Gifting groups
- B.) Investment clubs
- C.) Multilevel marketing business opportunities
- D.) All of the above

Do you think that someone you know (e.g., family member or friend) has ever been asked to join a pyramid scheme?

- Yes
- No

Do you think that you have ever been asked to join a pyramid scheme (i.e. been approached through social media or in-person to join what you believe is a pyramid scheme)? *

- Yes
- No


While all of the offers below may look suspicious, please review the images and look for those that show specific warning signs of a pyramid scheme.

Identify the offer(s) above that show specific signs of pyramid scheme fraud?

- Offer A
- Offer B
- Offer C
- Offer D
- Offer E

Options which had explicit warning signs of pyramid scheme fraud:

OFFER A



Making the Loom Spin
A Quick Guide to Gifting
 4 GIFT-GIVERS+2 COACHES+1 LEADER=1 TEAM on EACH side of the loom. Each team's goal is to "BLESS OUT" the receiver. When the RECEIVER is fully "BLESSED", they move out and the LEADERS become RECEIVERS on 2 NEW beards. Everyone moves IN a space filling in each section of the new beard.

GIVER--COACH--LEADER--RECEIVER

BLUE: Gift the receiver & learn how the loom works. YOU MUST BE COACHABLE, TEACHABLE AND DUPLICATABLE

GREEN: Make sure your BLUES are well-informed. Coach the BLUES on inviting 2 more givers

PINK: You are role models of the loom. Check on folks. Keep the energy high. Answer any questions and keep information updated in the Circle. Get your team ready for the split.

PURPLE: Celebrate! Keep your loom updated. Keep gift-receiving info updated & when you "BLESS OUT" GIVE THANKS and consider repeating as often as you would like

OFFER C

Anyone want to join in on this fun?

SECRET SISTER is back! I am looking for 6 or more ladies interested in a holiday gift exchange. Doesn't matter where you live- you are welcome to join. You have to buy one gift valued of at least \$10 and send it to your secret sis. You will then receive 6-36 gifts in return. This is so much fun! I loved sending a gift to a complete stranger knowing that she would have a bright apit in her day because of what I sent. Let me know if you're interested, and I will send you information about your sister. We could all use some happy mail! Who's in with me? Just comment "I'm in"

Like Comment Send

OFFER D



The 2&Go Program

Step 1: Buy an Affiliate Pack to get you started.

Step 2: Get on Auto-delivery to get your monthly supply of products and stay bonus qualified!

Step 3: Find 2 people who feel like you do, who want time and financial freedom. Teach them to follow the 2&Go program!

Options that do not have explicit warning signs of pyramid scheme fraud (while they may have warning signs of other issues):

OFFER B



Come to Paradise!

Enjoy a 4-Day, 3-Night Complimentary Luxury Resort Getaway FREE at a Beautiful Regal Queen Resort

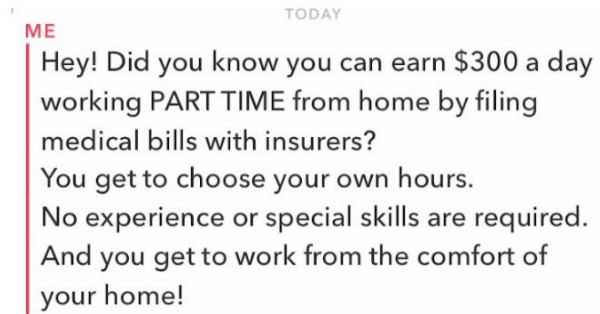
We need loyal, happy customers to tell family and friends about the wonderful time they had at our renovated Cancun resort! Regal Queen Resort Company is giving away FREE vacations to the first 500 callers that register today from your city.

WHAT'S THE CATCH?

There is no catch or purchase necessary to claim your free vacation. Simply cover the Government taxes of \$59 per person today to secure your trip and tell your friends about your vacation.

CALL NOW:
1-800-344-2850
REGALCANCUN.COM/FREETRIP

OFFER E



TODAY

ME

Hey! Did you know you can earn \$300 a day working PART TIME from home by filing medical bills with insurers? You get to choose your own hours. No experience or special skills are required. And you get to work from the comfort of your home!

A.2 Additional Lagged Survey Questions (i.e., for Time 2 and 3)

Have you been asked to join a pyramid scheme since the initial experiment (e.g., you have been approached through social media or in-person to join what you believe is a pyramid scheme)?

- Yes
- No

If you were asked to join a pyramid scheme, how did you respond? *

- Not applicable, I was never invited to join one.
- I responded with a “hard no,” such as “This sounds like a pyramid scheme” or “Sorry, I’m just not really interested in what this business has to offer.”
- I responded with a “soft no,” such as “I don’t have the time to join something like that” or “I will do some more research on the business, but I don’t think this is my kind of thing.”
- I was willing to hear additional information but ultimately didn’t join.
- Other: _____

Since you participated in the experiment, have you read or watched any additional educational material about pyramid schemes (for example, videos, news articles, etc.)?

- Yes
- No

Since you participated in the experiment, have you talked to any of your family members, friends or peers about pyramid schemes (for example, gave advice, discussed the implications of pyramid schemes, etc.)?

- Yes
- No

Financial Literacy and Student Debt: A Survey Analysis of University Students

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Student loan debt continues to be a significant financial burden for many young adults, especially among university students. This paper investigates the relationship between financial literacy and student loan indebtedness at a major state university. Through a survey conducted in 2024, we assess financial literacy and its correlation with student debt. The results reveal that students with loans have significantly lower financial literacy, particularly those with higher debt levels. Furthermore, these students report greater stress about their loans and feel less prepared to manage their debt. Our findings emphasize the need for improved financial literacy education to support better financial decision-making among students.

Keywords: Financial literacy, Student loans

Introduction

Affordability remains a significant concern for today's college students, with 67% of Generation Z (those born between 1996 and 2010) citing it as their primary worry regarding higher education (Hub). By the end of 2023, U.S. student loan debt had escalated to approximately \$1.727 trillion, constituting 6.31% of the nation's GDP, second only to mortgage debt (Yannelis & Tracey, 2022). This financial burden is borne by a large portion of young adults: 34% of individuals aged 18 to 29 report having student loan debt, with the average public university borrower accumulating \$32,637 in debt to obtain a bachelor's degree (Hanson, 2024).

While student loans have facilitated access to higher education for many students, they also pose a substantial challenge for those unable to secure post-graduation employment sufficient to repay their debts. Moreover, the increased availability of student loans has contributed to rising demand for university education, which, in turn, has led universities to increase tuition rates beyond the pace of inflation (Kargar & Mann, 2023; Lucca et al., 2019).

Even before the COVID-19 pandemic, delinquency rates on student loans were increasing. Federal student loans, which account for over 90% of all loans, do not require a credit check, making them a high-risk financial product (Aid, 2023). These loans were once guaranteed by the Federal Family Education Loan (FFEL) Program, which was discontinued in 2010, leading to the cessation of Wall Street banks securitizing these loans.

Federal efforts to address the student loan crisis have yielded limited progress. The Obama administration proposed covering community college costs and capping loan payments at 10% of borrowers' income (Administration, 2015). During the COVID-19 pandemic, federal student loan payments were suspended, with interest rates set at 0% through September 2023, as part of the COVID-19 Emergency Relief and Federal Student Aid (Aid, 2023). Although the Biden administration proposed forgiving up to \$10,000 in federal student loans and up to \$20,000 for

Pell Grant recipients, the U.S. Supreme Court ruled in June 2023 that the president lacked the authority to implement this plan (States, 2023). As an alternative, the administration introduced another plan called Saving on a Valuable Education (SAVE), which aims to reduce monthly payments and shorten repayment periods for eligible borrowers.

With the end of COVID-19-related forbearance, the default rate on federal student loans, which had fallen to 0.0% in 2023, is expected to rise sharply. As of 2023, 11.2% of adults with student loans reported missing at least one payment, signaling an impending rise in delinquencies (Welding, 2023). Rising interest rates are also causing loan balances to increase, exacerbating the financial pressure on borrowers.

Defaulting on a student loan has severe financial consequences for borrowers, affecting their credit scores, making borrowing either impossible or prohibitively expensive, and sometimes resulting in wage garnishment. In addition, unlike other consumer loans, student loans are usually non-dischargeable and, therefore, cannot be eliminated through personal bankruptcy (Looney & Yannelis, 2022). Thus, it is unsurprising that young adults are concerned about their student loan debts.

In this paper, we investigate student indebtedness among students of a major state university and its correlation with financial literacy. Our findings are based on a survey administered to undergraduate and graduate students on the campus of a major state public university in the spring of 2024.

Our paper contributes to several strands of literature, particularly in the area of student loans and financial literacy. Numerous studies have shown that student loans increased college enrollment, especially the enrolment of low-income students (Leslie & Brinkman, 1987; Sun & Yannelis, 2016). Some studies (Hansen, 1983), however, are less optimistic about the effect of loans on the enrollment of poorer students.

While previous research has primarily focused on the role of student loans in facilitating access to higher education and their impact on parental decisions and student behavior during later high school years, our study offers a different perspective. We examine the state of student loans across the student population, the characteristics of a typical public university borrower, and especially how financially literate borrowers are.

Financial literacy, the ability to understand and manage one's finances effectively, is essential for making informed financial decisions. Research consistently shows low levels of financial literacy among the U.S. population and worldwide (Bernheim, 1995; Hilgert, 2003; Lusardi, 2008, 2011c, 2014). Empirical studies demonstrate that financial literacy is strongly associated with various sociodemographic and personal characteristics such as gender, education, race, age, and income levels, with studies on youth, including high school and college students, showing particularly low levels of financial literacy within these groups (Annabi et al., 2018; BenDavid-Hadar, 2015; Chan et al., 2017; Chen, 1998; Lusardi et al., 2010; Mandell, 2008; Shim et al., 2010).

Inadequate financial literacy has been linked to suboptimal financial decision-making in several ways. Individuals with low levels of financial literacy tend to have lower wealth, plan less for retirement, incur higher transaction costs, pay higher interest rates on mortgages, and are less likely to participate in the stock market (Campbell, 2006; Christelis, 2010; Gerardi et al., 2013; Lusardi & de Bassa Scheresberg, 2013; Lusardi, 2008, 2007, 2011a, 2011b; Moore, 2003; O'Neill & Xiao, 2015; Stango, 2009; van Rooij, 2011).

Lusardi and Tufano (Lusardi & Tufano, 2015) examined the relationship between financial literacy and indebtedness. They found that individuals with higher levels of financial literacy were more likely to make informed borrowing decisions, resulting in lower borrowing costs. Moreover,

other studies document that financial literacy affects how students perceive their student loans. For example, Markle (Markle, 2019) found that students with higher financial literacy are more likely to view their student loans positively as an optimal financial decision and are less concerned about their ability to repay the loan. Family background also plays a crucial role in students' financial literacy (Shim et al., 2010; Xue & Chao, 2015), with many students choosing not to borrow due to a lack of understanding of loans, fear of debt, or underestimation of the value of a college education (Ackert et al., 2022; George-Jackson & Gast, 2015; McCabe & Jackson, 2016; Perna, 2006; Xue & Chao, 2015). Artavanis and Karra (Artavanis & Karra, 2021) documented that students with low financial literacy are more likely to underestimate future student loan payments and, consequently, are more vulnerable to default.

In essence, research indicates that financial literacy is crucial for making well-informed financial decisions, including student loans. It is imperative for students taking out loans to grasp both the positive and negative consequences of this decision, understand loan repayment, and recognize how the loan will impact their future borrowing capacity.

Based on our survey, we find that students with student loans have significantly lower financial literacy than students without loans. Furthermore, students with high levels of student debt tend to have even lower financial literacy than those with lower levels of debt.

An alarming discovery is that fewer than 17% of students burdened with high student debt feel adequately prepared by their major to repay their loans. Consequently, it's not surprising that they experience significantly more stress due to their debt.

The paper is organized as follows. Section 2 describes the survey administered to the students, and provides statistics on the collected data, including the statistics on respondents. Results and regression models are summarized in Section 3. Section 4 discusses the implications of our findings and concludes the paper.

Data

The data come from a survey administered to full-time students attending a major state university in Southeast U.S. with an enrollment of about 31,000 students. The survey was carried out in March-April 2024. The survey is anonymous and consists of three parts. The first part covers basic background variables such as gender, age, expected graduation year, and college.

The second part assesses information about student loans and the students' investment behavior. We ask whether the student has a student loan and the approximate size of the loan. We categorize loans into four size groups: under \$10,000, \$10,000 to \$50,000, \$50,000 to \$100,000, and above \$100,000. For the population of students that have a student loan, we further ask two questions: (1) "Do you feel that major prepared you to pay off your student loan?" and (2) "How stressed do you feel about paying off the loan?" (1 the least stressed to 10 the most stressed). In this part, we also ask questions about the investment behavior of students. However, the responses to these questions are not used in this study.

The third part tests the financial literacy of respondents. Lusardi and Mitchell designed a standard set of questions that evaluate the understanding of different concepts of investment decisions and saving, such as interest rates, inflation, and risk diversification (Lusardi, 2008, 2011a, 2011c). These questions are short, simple, relevant in day-to-day life, capture the understanding of general concepts, and allow for the differentiation of financial knowledge. Answers to these questions allow to quantitatively evaluate the financial literacy of respondents.

In more recent studies, additional questions were added to surveys. These questions concern compound interest, mortgages, and bonds.

In this study, we use a set of six multiple-choice questions used by the FINRA Foundation and administered periodically to the U.S. population. The financial literacy questions are shown in Table 1.

Table 1
Financial Literacy Questions

Topic	Question	Possible answers
Risk and diversification	Buying a single company's stock usually provides a safer return than a stock mutual fund.	a. True b. False c. Don't know d. Prefer not to say
Inflation and purchasing power	Imagine that the interest rate on your savings account was 1% per year, and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?	a. More than today b. Exactly the same c. Less than today d. Don't know e. Prefer not to say
Bond price	If interest rates rise, what will typically happen to bond prices?	a. They will rise b. They will fall c. They will stay the same d. There is no relationship between bond prices and interest rates e. Don't know f. Prefer not to say
Interest rate	Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?	a. More than \$102 b. Exactly \$102 c. Less than \$102 d. Don't know e. Prefer not to say
Compound interest	Suppose you owe \$1,000 on a loan, and the interest rate you are charged is 20% per year compounded annually. If you didn't pay anything off, at this interest rate, how many years would it take for the amount you owe to double?	a. Less than 2 years b. At least 2 years but less than 5 years c. At least 5 years but less than 10 years d. At least 10 years e. Don't know f. Prefer not to say
Mortgage	A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.	a. True b. False c. Don't know d. Prefer not to say

Note: The table shows questions used to quantitatively evaluate the financial literacy of respondents. Questions are adopted from the National Financial Capability Study administered periodically by FINRA Foundation to the U.S. population.

Table 2 shows summary statistics for variables from the survey used in this study. In total, 353 students responded to the survey. The sample is almost evenly divided between males and females, 45.3% and 54.1%, respectively (about half percent did not disclose their gender, Panel A). Most students were Caucasian (88.4%), 5.4% Black or African American, and 4% Asian. Other races were represented collectively by 2.3%. Almost 94% of respondents were undergraduate students. The respondents were freshmen (7.1%), sophomores (8.5%), juniors (45.1%), and seniors (39.4%).

Table 2
Descriptive Statistics

<i>Panel A: Demographic variables</i>		
Gender	Male	45.33%
	Female	54.11%
	Prefer not to say	0.57%
Race	Caucasian	88.39%
	Black or African American	5.38%
	Asian	3.97%
	Others	2.26%
	Student type	Undergraduate
	Graduate	6.34%
Graduation year	Freshman	7.07%
	Sophomore	8.50%
	Junior	45.05%
	Senior	39.38%
	<i>Panel B: Student loans</i>	
Do you have a student loan?	No student loans	73.64%
	Under \$10,000	6.97%
	\$10,000 to \$50,000	12.42%
	\$50,000 to \$100,000	5.15%
	Over \$100,000	1.82%
Did the major prepare you to pay your loan?	Yes	44.55%
	No	23.64%
	Unsure	31.82%
<i>Panel C: Financial literacy</i>		
Risk and diversification	Correct	46.18%
Inflation and purchasing power	Correct	54.67%
Bond price	Correct	39.94%
Interest rate	Correct	64.59%
Compound interest	Correct	36.83%
Mortgage	Correct	53.82%
	All correct	14.45%
	At least 4 correct	46.18%

Note: The table shows descriptive statistics of variables used in the study. Data was collected from a survey of university students.

Based on our survey data, 26.3% of students (Panel B) report having a student loan. The majority of respondents with student loans borrow between \$10,000 and \$50,000 (36.2% of borrowers), and about 5.7% of students borrow over \$100,000 (representing 1.82% in the overall sample and 1.81% for undergraduate students).

The national average of undergraduate (graduate) students with federal student loans is 29% and 7.3% from private sources. In our survey, 31.72% of undergraduate students report having a student loan. This number is comparable with the national average since students using private lenders are likely to use federal loans as well.

Panel C summarizes answers to financial literacy questions. Overall, the performance on financial literacy questions is poor. Only about 14.5% of respondents answer all financial literacy questions correctly. Assuming that a financially literate individual is an individual who answers at least four out of these six questions correctly, only 46% of students are financially literate. It is comparable to the findings of Artavanis and Karra who estimated a financially literate student population of around 40% using a survey in a major public university in Massachusetts ((Artavanis & Karra, 2021).

The distribution of correct and incorrect answers is different across questions. The easiest questions seem to be questions concerning simple interest, diversification, and inflation. For example, only about one-third of respondents failed to provide a correct answer to the questions on simple interest, and about half to the questions about risk and diversification, and inflation and purchasing power. Questions with the least correct answers are questions about compound interest (36.8%) and bond prices (39.9%). The question about compound interest requires more mathematical skills and is also used to evaluate the numeracy of respondents (see, for example, (Almenberg & Widmark, 2011) linking financial literacy with numeracy skills. Question about bond prices requires at least basic familiarity with bonds and therefore may be difficult, especially for young people from other than business backgrounds.

Results

The primary objective of this paper is to assess the financial literacy of students with student loans. Panel A of Table 3 presents the mean number of correct responses to financial literacy questions for students with and without student loans. On average, students with loans demonstrate lower financial literacy than those without loans, answering 2.62 questions correctly compared to 3.12 for students without loans. This difference is statistically significant at the 5% level.

Panel B further examines financial literacy across students with varying loan amounts, perceptions of their preparedness to repay the loans based on their major, and the stress associated with carrying student loans. Students with larger loan balances tend to exhibit lower financial literacy than those with smaller loans, though this difference is not statistically significant. However, students with larger loans feel significantly less prepared by their major to repay their debt and experience higher levels of stress regarding their loans.

Table 3
Means of Variables among Different Populations of Students Based on Student Loans

	Number of correct financial literacy questions	Students feeling prepared	Loan stress
<i>Panel A: Student loans (all student population)</i>			
No student loans	3.12		
Students with loans	2.62		
Difference	0.50**		
<i>Panel B: Loan size (only population of students with student loans)</i>			
(1) \$Under \$10,000	2.91	56.52%	4.21
(2) \$10,000 to \$50,000	2.88	48.78%	5.63
(3) \$50,000 to \$100,000	2.88	64.70%	6.76
(4) Over \$100,000	1.83	16.66%	7.00
Difference (1)-(5)	1.08	39.89%**	-2.78**
<i>Panel C: Financial literate (only population of students with student loans)</i>			
Yes	4.79	50.00%	4.71
No	1.47	41.67%	5.68
Difference	3.32***	8.33%	-0.97*

To explore how financial literacy influences the likelihood of having a student loan, we estimate a probit regression model:

$$Loan_i = \alpha + \beta_1 \times Financial\ Literacy_i + \sum_{k=1}^n \gamma_k \times Controls_i + \varepsilon_i \quad (1)$$

where $Loan_i$ is a binary variable that takes the value of 1 if a student has a student loan and 0 otherwise. $Financial\ Literacy_i$ is measured by two variables: (1) the total number of correct answers to financial literacy questions, and (2) a dummy variable indicating whether the student correctly answered at least 4 out of 6 questions. The control variables include gender, race, and year of graduation, with the subscript i denoting the individual respondent and, ε_i representing the error term.

Table 4 summarizes the probit regression results. Models (1) and (2) focus on undergraduate students, while Models (3) and (4) include both undergraduate and graduate students. The findings are consistent across all models and financial literacy measures: students with higher financial literacy are significantly less likely to have student loans. Specifically, for undergraduate students, each additional correct answer is associated with a 2.5% reduction in the probability of having a loan and financially literate students are 14.6% less likely to have student loans.

The probit regression also indicates that Black or African American students are significantly more likely to have student loans, with an increased likelihood of 31–32%. This outcome may be influenced by the generally lower household incomes within minority groups. Students from lower-income families are often more reliant on loans to finance their education. Previous research by (Lusardi & Mitchell, 2007) has shown that lower-income households tend to have lower financial literacy. To ensure that our results are not driven by the lower financial literacy of students from economically disadvantaged backgrounds, we incorporate Pell Grant data from individual

colleges. The Pell Grant is a federal aid program that primarily serves students from families with incomes below \$50,000.

Table 4
Likelihood of a Student Having a Student Loan

	Undergraduate students		All students	
	Model (1)	Model (2)	Model (1)	Model (2)
<i>Financial literacy variable</i>				
Correct answers	-0.0750***		-0.0788**	
Financially literate		-0.4383***		-0.4450***
<i>Control variables</i>				
Female	0.0831	0.0496	0.0230	-0.0005
Black	0.9652***	0.9315***	0.8649***	0.8457***
Asian	-0.6160	-0.6306	-0.6838	-0.6900
Graduation year	-0.2330***	-0.2320***	-0.2312***	-0.2305***
Const.	0.0755	0.0678	0.1053	0.0890
N	331	331	353	353
Pseudo R ²	0.0527	0.0618	0.0508	0.0596
Chi ²	21.79	25.58	22.23	26.10

Note: The table reports the results of probit regression according to equation (1):

$$Loan_i = \alpha + \beta_1 \times Financial\ Literacy_i + \sum_{k=1}^n \gamma_k \times Controls_i + \varepsilon_i$$

where $Loan_i$ takes a value of 1 if a student has a student loan or 0 if the student does not have a loan. $Financial\ Literacy_i$ proxies for the respondent's financial literacy. Two measures of financial literacy are: (1) *Correct answers* is the number of correct answers to literacy questions and (2) *Financially literate* is a dummy variable equal to 1 if a respondent answers at least 4 out of 6 questions correctly, 0 otherwise. We control for gender, race, and graduation year.

*** and ** denote significance at 99% and 95% levels, resp.

We categorize students into Low and High Resource groups and Low and High Financial Literacy groups based on the median percentages of Pell Grant recipients at each college and the median number of correct financial literacy responses.

Table 5 displays the percentage of students with loans across these groups. As expected, students from low-resource backgrounds are more dependent on loans. However, regardless of resource level, students with lower financial literacy are more likely to have loans. In the low-resource category, students with lower financial literacy are nearly twice as likely to have loans compared to their financially literate peers (42% vs. 24%). This gap widens within the high-resource group, where students with low financial literacy are more than four times as likely to have loans (26% vs. 6%).

Table 5
Percentages of Students with Student Loans within Resource Level and Financial Literacy Categories

		Resource Level	
		Low	High
Financial Literacy	Low	42%	26%
	High	24%	6%

Note: The table reports the percentage of students who have student loans based on their financial literacy and resource level categories. Students are categorized into Low and High Resource groups and Low and High Financial Literacy groups based on the median percentages of Pell Grant recipients at each college and the median number of correct financial literacy responses.

We further incorporate the percentage of Pell Grant recipients by college into the regression analysis. As reported in Table 6, financial literacy remains a highly significant predictor of student loan status across all models.

Table 6
Likelihood of a Student Having a Student Loan Adjusted for Resource Level

	Undergraduate students		All students	
	Model (1)	Model (2)	Model (1)	Model (2)
Financial literacy variables				
Correct answers	-0.0787**		-0.0841**	
Financially literate		-0.4489***		-0.4641***
Control variables	Yes	Yes	Yes	Yes
N	331	331	353	353
Pseudo R ²	0.0555	0.0646	0.0561	0.0651
Chi ²	22.94	26.70	24.57	28.50

Note: The table reports the results of probit regression according to equation (1):

$$Loan_i = \alpha + \beta_1 \times Financial\ Literacy_i + \sum_{k=1}^n \gamma_k \times Controls_i + \varepsilon_i$$

where $Loan_i$ takes a value of 1 if a student has a student loan or 0 if the student does not have a loan. $Financial\ Literacy_i$ proxies for the respondent's financial literacy. Two measures of financial literacy are: (1) *Correct answers* is the number of correct answers to literacy questions and (2) *Financially literate* is a dummy variable equal to 1 if a respondent answers at least 4 out of 6 questions correctly, 0 otherwise. We control for gender, race, graduation year, and the percentage of Pell Grant recipients by colleges.

*** and ** denote significance at 99% and 95% levels, resp.

Conclusion

The escalating cost of higher education has led to an increased dependence on student loans to finance college education, resulting in student loan debt becoming a significant financial burden for many young adults.

In our study, we surveyed students from a major state university in the Southeast about student debt and assessed their financial literacy. Nearly one-third of the students reported having student debt. We found that financial literacy was significantly lower among students with student debt, particularly those with high levels of debt (exceeding \$100,000). Moreover, students with higher student loans report significantly more stress about their debt and feel significantly less prepared by their major to manage their student debt.

These results are concerning as they indicate that some students may not fully grasp the implications of taking out student loans when they initiate them. Furthermore, they may have incorrect expectations about their university education. Taking out a student loan is a complex decision and may be overwhelming, especially for young people. They must consider the benefits of university education and the expected income after graduation, balanced against the responsibility of future loan repayments. Students with higher levels of financial literacy are more likely to make informed decisions and reap the benefits of their loans. Therefore, it is imperative to prioritize efforts to improve financial literacy among high school and college students to address student loan debt and promote their financial well-being.

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Beyond the Numbers: Enhancing Learning Through Reflection in Finance

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Reflection has long been recognized as a valuable tool for enhancing learning in higher education; however, analytical disciplines like finance have been slower to adopt reflective practices. Utilizing an IRB-approved experiment across two universities, we evaluate the impact of structured reflection on student performance in an analytical-based introductory finance course. We find that the act of exam reflection has significant positive effects on student performance, highlighting its potential benefits in analytical classrooms. As the AACSB emphasizes deeper learning, we present a pedagogical framework that faculty in analytical courses can implement to foster metacognition and improve student outcomes through exam reflection.

Keywords: financial education, reflection, introductory finance, self-assessment, undergraduate education

Introduction

Reflection, a cognitive process involving the derivation of meaning from experience, thinking to learn, and learning through questioning (Loughran, 2002; Rogers, 2001), is essential for deep learning. Rogers (2001) describes reflection as a process that enables learners to integrate their understanding into their experiences, allowing them to make better choices and take more effective actions in the future. As educators place greater emphasis on Bloom's Taxonomy of Learning and metacognition, we conduct an experiment to assess the benefits of structured reflection in introductory finance courses. Specifically, we investigate whether structured reflection can better guide students in modifying their behavior to improve future performance. To our knowledge, this is the first study to evaluate the impact of reflection on student performance in the finance classroom.

The Association to Advance Collegiate Schools of Business (AACSB) emphasizes accountability and continuous improvement as the foundation of its accreditation standards (AACSB, 2013). At the same time, the AACSB encourages pedagogical methods that promote deeper levels of learning. Reflective practices support this goal by fostering complex cognitive processes (Lau, 2016) and aligning with the AACSB's emphasis on pedagogical methods that foster deeper levels of learning. By incorporating critical reflection into the curriculum, educators can empower students not only to acquire knowledge but also to engage with their own learning processes, leading to a more meaningful and comprehensive educational experience.

To evaluate the value of reflection, we conducted an IRB-approved classroom experiment at two universities. At both institutions, introductory finance students were randomly assigned to control and experimental groups based on their course section. Students in the experimental group

were required to reflect in written form on their exam performance and study methods after each exam. The goal of this reflection was to transform past performance into a learning experience through the process of assessment (Hoo et al., 2020). As part of the reflective process, students evaluated their performance, identified areas for improvement, and considered alternative strategies for future exams. By comparing subsequent exam and course performance, we sought to determine whether reflection could positively impact learning in an analytical-based higher education learning environment. Our findings suggest that reflective practices are indeed associated with improved student performance and increased self-awareness of learning and thinking processes, ultimately leading to better course outcomes.

This study distinguishes itself from previous research on reflection by focusing on its application in an analytical context, emphasizing the effects of reflection on performance rather than the theory behind reflection. Our findings contribute to the existing body of knowledge on reflection in higher education and provide valuable insights into factors influencing student performance in introductory finance classes. The remainder of this paper is organized as follows: we present the theoretical foundations of both reflection and success in introductory finance courses; our methodology is explained; results of our analysis are presented; and finally, we conclude.

Theoretical Foundations

The literature on the value of reflection in education is well developed. First introduced by Dewey (1910), reflective thought is a process of “active, persistent, and careful consideration of any belief.” Loughran (2002) further emphasizes the importance of reflection by explaining that “experience alone does not lead to learning; reflection on experience is essential.” However, the literature consensus is that simply instructing students to reflect is insufficient. Effective reflection requires guidance in connecting experiences and challenging assumptions and beliefs (Ash & Clayton, 2004).

Rodgers (2002) builds upon Dewey’s (1910) work to provide a comprehensive definition of reflection. She summarizes Dewey’s findings into four key criteria for effective reflection: it must result in understanding, be systematic, occur through interaction, and lead to personal growth and change. Rodgers further defines six phases of reflection: (1) the experience itself, (2) spontaneous interpretation of the experience, (3) identifying problems arising from the experience, (4) generating possible explanations, (5) analyzing explanations to develop solutions, and (6) testing the developed solutions. Our study is grounded in this six-phase framework.

Additionally, two widely recognized models further inform our approach: Gibbs’ Reflective Cycle and Schön’s Reflection Model. Gibbs (1988) introduced a structured cyclical model that guides learners through six stages of reflection: (1) Description, (2) Feelings, (3) Evaluation, (4) Analysis, (5) Conclusion, and (6) Action Plan. This model emphasizes the importance of learning from experience by systematically analyzing both successes and challenges. Meanwhile, Schön (1983) differentiates between reflection-in-action (thinking on one’s feet during an experience) and reflection-on-action (analyzing past experiences to improve future performance). In the context of finance education, reflection-on-action is particularly relevant, as students analyze their exam performance to refine their learning strategies.

More recent work in higher education explicitly links reflection to metacognition, which is the process by which learners monitor, evaluate, and adjust their own thinking and study behaviors. Zimmerman (2002) demonstrates that self-regulated learning depends on a cycle of reflection,

planning, and behavioral adjustment, providing a theoretical foundation for studying reflection as part of the learning process. Ambrose et al. (2010) similarly argue that structured reflection activities help students recognize ineffective learning approaches and adopt more productive strategies, thereby improving how they approach studying. Tanner (2012) further describes metacognitive reflection as a mechanism for improving students' ability to plan, assess, and revise their learning strategies, particularly in courses that require students to actively engage with the material.

A growing body of research specifically examines exam wrappers, structured reflection activities completed after assessments that prompt students to analyze their preparation strategies, exam performance, and plans for improvement. Lovett (2013) shows that exam wrappers can encourage students to reflect on how they studied and identify more effective strategies for future assessments. Empirical studies further demonstrate that such structured assessment reflections can strengthen metacognitive awareness and promote more effective study behaviors across subsequent exams (Gezer-Templeton et al., 2017; Hodges et al., 2020; Pate et al., 2019; Soicher & Gurung, 2017). Classroom-based evidence also suggests that prompting students to reflect on the purpose of assigned work can deepen conceptual understanding and help students identify effective study strategies that improve retention and performance (Chakraborti & Pradhan, 2023).

Taken together, this literature supports viewing structured reflection as a way for students to think more deliberately about their learning and adjust their study behaviors accordingly. While exam wrapper research has been widely applied in STEM and science education, comparatively little work has examined structured assessment reflection in finance and other analytically intensive business disciplines. This study contributes to that literature by examining the role of structured exam reflection in a quantitative finance course. Recent integrative work further emphasizes that metacognitive reflection is conceptually distinct from general reflection and requires structured prompts that engage monitoring and regulation of cognition, rather than unguided self-expression (Merkebu et al., 2023; Merkebu et al., 2024).

Despite its potential benefits, student reflection often faces implementation challenges in higher education (Sandars, 2009), including low engagement and motivation, difficulty navigating the reflection process, and a lack of integration with teaching and learning. While Sandars (2009) focuses on medical education, these challenges are relevant across higher education. To mitigate low engagement, we incorporated a grade component to motivate students; however, the quality of reflection may still reflect the challenges identified by Sandars (2009).

The literature offers limited insights into the effectiveness of reflection across different subject areas. While Sandars (2009) evaluates medical students and Wagenheim (2005) examines reflection broadly in business education, questions remain about its impact across disciplines. Specifically, it is unclear whether reflection has the same effect in analytical subjects as in non-analytical ones. Our study contributes to this discussion by examining the role of reflection in a quantitative learning environment.

Beyond reflection, the literature has established several other determinants of student success in introductory business courses, including accounting and economics, in addition to finance, the focus of our study. Eskew and Faley (1988) model student performance in introductory accounting courses, and find that SAT scores, high school and collegiate grades, the number of quizzes taken, previous accounting or related experience, and academic level influence exam performance. Aptitude, proxied for by SAT scores, and effort, proxied for by the number of quizzes taken, have the most significant impact on student outcomes.

Raimondo et al. (1990) further explore factors influencing performance in introductory economics courses, comparing large (200 – 350 students) and small (25 - 35 students) lecture sections. Their findings indicate that students in smaller sections achieve higher grades, adding to the understanding of how class size affects learning outcomes.

In the context of introductory finance courses, Borde et al. (1998) analyze student characteristics and performance, controlling for gender, age, transfer status, student organization involvement, the number of hours a student works, and prerequisite accounting course grades. They find that males, on average, outperform females, and transfer students from community colleges tend to perform worse than those who began their studies at the university where they took the course. Additionally, GPA is a strong predictor of success, with higher-GPA students performing better.

Consistent with Borde et al. (1998), Nofsinger and Petry (1999) find that study time and GPA are the strongest predictors of finance exam performance. Trine and Griepentrog (1999) add that the perceived effectiveness of the student's study approach is also a key factor. Using a larger sample size, Terry (2002) supports Borde et al.'s findings, showing that student performance is significantly related to gender, GPA, and grades in prerequisite courses, with major selection also playing a role.

Wilson (2002) evaluates exogenous determinants of student performance in introductory finance courses, where exams are standardized, but instructors assign final grades at their discretion. He finds that while class size does not affect objective performance, it does impact final course grades assigned by the instructor. Additionally, students in longer-duration classes score higher on exams, though this does not necessarily translate into higher assigned grades.

More recent work in finance education reinforces these findings and extends them to a wider range of student characteristics and course designs. Pilloff and Kling (2017) find that prior GPA and quantitative preparation explain a substantial share of the variation in introductory finance course grades, while certain student characteristics such as employment intensity and prior course exposure are also associated with performance. Biktimirov and Armstrong (2015) document that students who repeat introductory finance typically improve their performance, although on average they do not fully close the gap with peers who pass on the first attempt. Akimov et al. (2018) analyze determinants of student success in finance courses and confirm that GPA, prior quantitative coursework, and continuous assessment results are strong predictors of outcomes. In addition, Knewton (2018) finds that more frequent online quizzes and homework are positively related to final exam scores in Principles of Finance, highlighting the role of structured practice and timely feedback in promoting learning. Taken together, these studies provide support for the importance of academic preparation, student effort, and course design in explaining student performance in finance courses and motivate our inclusion of GPA, prior coursework, work hours, and study effort as control variables in the empirical analysis.

Methodology

This study examines the impact of structured exam reflection on student performance in an introductory finance course. We propose that exam reflection enhances student performance by prompting students to analyze their learning processes and adjust their study strategies for future exams. Our structured reflection process encourages students to move beyond simply recognizing their exam performance to understanding why they performed as they did (Perusso et al., 2020). This study utilizes critical reflection, a form of meta-reflection in which students assess their

actions and consider necessary changes to improve learning outcomes (Perusso et al., 2020). By engaging in this process, students evaluate their competencies and assess their learning performance, fostering metacognition (Mok et al., 2006).

To determine the impact of reflection on student success in an introductory finance course, we conducted an IRB-approved experiment across two public universities. Both universities are urban institutions, and the courses were taught by finance professors with Ph.D.s from the same institution. Additionally, both Colleges of Business (COB) are AACSB accredited, and the courses are math intensive and taught as core required courses for all COB undergraduate students and offered by the Department of Accounting & Finance at both universities.

We implemented control and experimental groups at each university, with entire classes designated as either a control or experimental group. Groups were randomly assigned by coin toss. Each university had one experimental group and one control group per semester. The control groups completed a questionnaire collecting basic personal and academic information, but they were not asked to reflect on their study habits or exam performance.

In contrast, the experimental groups answered the same basic demographic and academic questions but also engaged in structured reflection. They were asked to consider how they studied for the exam, how prepared they felt, and what they would change for future exams. The questionnaires were administered after the first and second exams out of three total exams in the course.

In addition to student reflections, we collected demographic data, including gender, class standing, GPA, major, transfer student status, marital status including children, work hours, and total study hours for the course. Prior research (e.g., Borde et al., 1998; Eskew & Faley, 1988; Nofsinger & Petry, 1999; Terry, 2002) has identified these factors as significant determinants of course performance. Marital status and parental responsibilities may influence study habits, time management, and overall academic performance in either direction, potentially enhancing performance through greater discipline and time management or hindering it due to increased external demands. Given that the subject institutions serve a higher proportion of non-traditional students, these factors were especially relevant in understanding potential differences in reflective engagement and learning outcomes. Ethical considerations were addressed through IRB approval, ensuring voluntary participation and anonymity of student responses.

The experimental group answered eight reflection-based questions, designed using the six phases of reflection detailed by Rodgers (2002) and based on Dewey's (1910) foundational work. In our study, Phase 1, the experience, is centered on the exams taken by our students. We detail the remaining phases of reflection in relation to the eight questions we asked our students below.

Q1: What grade do you expect to earn on this exam?

This question is designed to focus on Phase 2 which requires a "spontaneous interpretation of the experience" (Rodgers, 2002, p. 851). This is the initial phase of reflection and helps students begin processing their performance.

Q2: Upon arriving to take the exam, did you feel that there were still subject areas you did not understand?

This question aligns with Phase 3 which is described as, "Naming the problem or the question that arises out of the experience" (Rodgers, 2002, p. 851). Specifically, the student can identify knowledge gaps and areas of uncertainty while assessing their preparedness.

Q3: Did you think this exam was easy, easy with a few difficult questions, moderate, moderate with a few easy questions, moderate with a few hard questions, hard with a few easy questions, or hard?

Having students quantify the difficulty of the exam helps them to further name the problem (Phase 3). Overall perceived difficulty of the material may help students identify specific challenges.

Q4: How many hours did you spend specifically studying for this exam?

This question aligns with Phase 4 of reflection, “Generate possible explanations for the problem or question” (Rodgers, 2002, p. 851). By having the students identify the number of hours they spent studying for the exam, students may begin to identify why they had problems with the exam and what caused them to feel prepared or unprepared for the exam. If they can provide an explanation for why they felt unprepared for the exam, this will help them connect poor performance with preparation time.

Q5: Please tell me how you prepared and studied for this exam.

This question further enables students to generate possible explanations for the problem by encouraging students to analyze their study methods and their effectiveness (Phase 4).

Q6: Based on how you studied for this exam, do you think it was the best way to approach the exam? Would you change anything?

Focusing on Phase 5 of reflection, this question requires that students evaluate their studying, which could be the cause of the difficulty they had with the exam, and use this to develop explanations which will help identify solutions. After determining the reasons for their exam performance, they are asked to provide suggestions that would help improve their performance. We then test if their suggestions were successful (Phase 6) by evaluating performance on the next exam.

Q7: What do you like about the course delivery method?

Q8: What do you not like about the course delivery method?

Questions 7 and 8 provide further opportunities for students to identify why they performed as they did on the exam (Phase 5), allowing students to reflect on how the course structure impacts their learning and study strategies and, as a result, alter their practices to improve future performance (Phase 6).

Questions 5 through 8 are open-ended questions in which the students were required to provide at least two complete sentences. We utilize a count of the total number of words in the response as an indicator of reflection engagement, recognizing its limitations as a measure of reflection quality. Additionally, we create an indicator variable equal to 1 if the student believed their study method was optimal and we create another indicator variable equal to 1 if the student indicated they would modify their study methods prior to the next exam. We also create additional indicators based on the responses, such as whether students referenced the course speed, study techniques (e.g., using homework), or reliance on class materials (e.g., slides/notes).

Data and Analysis

Summary Statistics

Our full sample consists of 302 students; however, due to attrition from students dropping the course, declining to participate in the study, or not completing portions of the reflection, we report results for 281 to 295 students, depending on the analysis. Examining the composition of our sample, we find that 50.00% of students are female, while accounting and finance majors make up 27.48%. Transfer students represent a majority at 53.64%. The class distribution includes Sophomores, Juniors, Seniors, and students classified as “Senior +” (those enrolled at the university for more than four years). Specifically, 30.79% of students in the sample are Juniors, 48.34% are Seniors, 18.87% are Senior + and the remainder are Sophomores. These statistics are summarized in Table 1.

We also evaluate GPA and exam scores across the full sample, as well as for the experimental and control groups. The sample’s average GPA is 3.28, with a mean GPA of 3.27 for the experimental group and 3.29 for the control group. The difference in these means is not statistically significant ($p > 0.05$). As indicated in Table 1, exam scores for Exam 1, Exam 2, and Exam 3 show similar distributions across the experimental and control groups, with Exam 3 exhibiting the largest difference: an average score of 79.59% in the control group versus 77.25% in the experimental group.

To further investigate potential differences, we divide the sample by university and then by experimental versus control group. Consistent with the full sample analysis, the results of our t-tests do not indicate any statistically significant differences between the experimental and control groups within each university (Table 1).

Regression Results

For our baseline regression, we estimate weighted least squares (WLS) Model (1) using the following specification:

$$\begin{aligned} \text{Grade}_{ij} = & \text{Univ}_j + \text{Gender}_j + \text{Year}_j + \text{GPA}_j + \text{AcctFinMajor}_j + \text{Transfer}_j \\ & + \text{WorkHrs}_j + \text{StudyHrs}_j + \text{HW}_{ij} + \text{Attendance}_{ij} \\ & + i. \text{MaritalStatus}_j + \epsilon \end{aligned} \tag{1}$$

Grade is the grade earned on Exam i by student j . We also include the final course grade as a dependent variable in our regressions in addition to the three exam grades. Univ is an indicator variable used to control for unobserved differences between the two universities and professors participating in the experiment. Gender is an indicator equal to 1 if the student is female. Year represents the number of years the student has completed post-Sophomore year. GPA is the student’s self-reported GPA. AcctFinMajor is an indicator equal to 1 if the student is an accounting or finance major. Transfer denotes whether the student transferred from a community college or another university. WorkHrs is the number of hours a week a student is employed. StudyHrs is the total amount of time the student spends reading, doing homework, and studying for the course each week throughout the semester. HW reflects student j ’s homework score for Exam i or, for final course grades, the total homework grade across the course. Attendance captures in-class attendance for each exam’s material, or total attendance for final grades. MaritalStatus is a set of

Table 1
Summary Statistics

This table reports summary statistics for the full sample and by university. Italicized rows report p-values from two-sample t-tests comparing experimental and control groups within the full sample and within each university.

	Total Group	Full Sample		University 1		University 2	
		Experimental	Control Group	Experimental	Control	Experimental	Control
Participants (count)	302	146	156	90	94	56	62
Females	50.00%	54.11%	46.15%	53.33%	47.87%	55.36%	43.55%
Acc & Fin Majors	27.48%	30.82%	24.36%	31.11%	19.15%	30.36%	32.26%
Transfer Students	53.64%	53.42%	53.85%	52.22%	50.00%	55.36%	59.68%
Class							
Sophomore	1.99%	2.74%	1.28%	4.44%	2.13%	0.00%	0.00%
Junior	30.79%	28.08%	33.33%	23.33%	29.79%	35.71%	38.71%
Senior	48.34%	50.00%	46.79%	55.56%	52.13%	41.07%	38.71%
Senior +	18.87%	19.18%	18.59%	16.67%	15.96%	23.21%	22.58%
Mean GPA	3.28	3.27	3.29	3.37	3.42	3.11	3.07
<i>p-value</i>			<i>0.7700</i>		<i>0.3302</i>		<i>0.5770</i>
Exam 1 Mean	81.89%	81.27%	82.47%	84.67%	86.21%	75.80%	76.80%
<i>p-value</i>			<i>0.4305</i>		<i>0.3177</i>		<i>0.7493</i>
Exam 2 Mean	81.51%	81.22%	81.78%	78.99%	81.02%	84.81%	82.94%
<i>p-value</i>			<i>0.7629</i>		<i>0.4334</i>		<i>0.4447</i>
Exam 3 Mean	78.46%	77.25%	79.59%	80.61%	83.86%	71.87%	73.11%
<i>p-value</i>			<i>0.3661</i>		<i>0.5239</i>		<i>0.4899</i>
Mean Final Grade	84.77%	84.87%	84.68%	84.54%	86.04%	85.41%	82.62%
<i>p-value</i>			<i>0.8931</i>		<i>0.3697</i>		<i>0.2784</i>

indicator variables distinguishing single students, single students with children, married students, and married students with children.

The results of our baseline regression analyses for each exam and the final course grade are provided in Table 2. Columns 1 through 3 utilize the grades of the first three exams as the dependent variable and column 4 evaluates the final course grade. As indicated by the significant coefficient on university in columns 1 (positive), 2 (negative), and 4 (negative), there are significant differences between exam scores and final grades for participating universities. This is not surprising given structural differences in the courses and variations in exam content. Consistent with prior literature, we observe a positive relation between student GPA and exam grades. Similarly, we find that students' homework performance positively predicts scores on Exam 1, Exam 3, and final grades, as indicated by the positive coefficient on HW in columns 1, 3, and 4. For Exam 3, we observe a negative relation between work hours and performance, though no significant relation is observed for the other exams. Interestingly, we observe a negative relation between self-reported study hours and exam scores, an unexpected finding. Additionally, we observe a positive relation between marital status (married, with or without children) and exam performance, potentially reflecting increased responsibility and maturity. As anticipated, we observe a positive relation between attendance and exam scores and final grades.

An additional pattern in Table 2 is the changing sign and significance of the UNIV indicator across outcomes. The coefficient is positive and statistically significant for Exam 1, but negative and significant for Exam 2 and the final course grade. Because UNIV captures institutional and course-structure differences rather than inherent student ability, these sign changes likely reflect differences in course design, assessment structure, and instructional sequencing between the two participating institutions. For example, Exam 1 at one institution may emphasize foundational material more closely aligned with prerequisite preparation, whereas later assessments may place greater weight on cumulative or application-based content. Differences in exam construction, grading weight distribution, attendance expectations, or pacing of quantitative topics could therefore influence performance at different points in the semester in opposite directions. Importantly, these institutional effects are controlled for in all models and do not alter the central finding that structured reflection is positively associated with subsequent exam performance. Instead, the UNIV coefficients underscore that student outcomes are shaped not only by individual characteristics and study behaviors, but also by contextual features of course implementation across institutions.

Another noteworthy result in Table 2 is the negative and statistically significant association between self-reported study hours and exam performance. Although this finding appears counterintuitive, it may reflect differences in the quality and timing of study rather than the quantity alone. Students who struggle with course material may report spending more time studying because they are reacting to difficulty, not because their study strategies are efficient. In contrast, students with stronger prior preparation or more effective problem-solving approaches may require fewer hours to achieve higher performance. Self-reported study time may also capture passive or less structured study behaviors, which prior learning research suggests are less effective than targeted practice and application. Thus, the negative coefficient should not be interpreted as evidence that studying is harmful, but rather that time spent studying does not necessarily translate into improved outcomes without effective learning strategies.

Table 2
Baseline Regression Results

Regression results from WLS regressions for exam grades, specifically for *Exam 1*, *Exam 2*, and *Exam 3*, and for the total course grade, *Final Grade*. The WLS regression model is defined in Model (1). *Univ* is an indicator equal to 1 for University 1 and 0 for the other; *Gender* is an indicator equal to 1 if the student is a female and 0 for a male; *Year* is the number of years the student has completed post sophomore year; *AcctFinMajor* is an indicator equal to one if the student is either an accounting or a finance major; *Transfer* is an indicator equal to 1 if the student transferred in from another university or community college and 0 if they began their freshman year at University 1 or 2; *GPA* is the student's self-reported GPA; *WorkHrs* is the number of hours a week a student is employed per week; *StudyHrs* is the amount of hours a week the student spends on the class, outside of exam studying; and *HW* is the grade that corresponds to the homework specific to the exam with the final grade homework being the total homework score for all homework. *Attendance* is the percent class attendance for the specified exam or entire course. *, **, *** denote the significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Exam 1	(2) Exam 2	(3) Exam 3	(4) Final Grade
Univ	4.191*** (1.352)	-5.943*** (1.368)	-0.0938 (1.585)	-3.072*** (1.162)
Gender	1.245 (1.139)	3.440*** (1.304)	0.599 (1.415)	0.467 (0.973)
Year	-1.088 (0.892)	-2.110** (1.012)	-1.752 (1.119)	-1.470* (0.789)
AcctFinMajor	0.836 (1.254)	-0.490 (1.405)	4.172*** (1.551)	1.268 (1.066)
Transfer	0.602 (1.205)	-1.624 (1.375)	-1.161 (1.490)	-1.096 (1.031)
GPA	11.67*** (1.583)	13.21*** (1.715)	9.213*** (1.967)	13.60*** (1.362)
WorkHrs	0.0184 (0.0419)	-0.0700 (0.0464)	-0.0904* (0.0489)	-0.0385 (0.0352)
StudyHrs	-0.805** (0.331)	-0.675* (0.372)	-0.802* (0.410)	-0.182 (0.282)
HW	0.525*** (0.163)	0.172 (0.676)	39.13*** (7.367)	0.0232* (0.0130)
Attendance	12.47 (7.622)	25.87*** (7.470)	9.626* (5.365)	17.58** (7.299)
Single w/ kids	-2.569 (3.406)	-7.193 (4.970)	-1.841 (4.366)	-1.080 (3.264)
Married w/out kids	5.556 (3.388)	6.131* (3.256)	13.52*** (3.626)	7.368*** (2.678)
Married w/ kids	7.559*** (2.142)	7.409*** (2.658)	7.864*** (2.809)	3.928 (2.718)
Constant	30.63*** (8.334)	23.76*** (8.758)	12.14 (9.532)	29.12*** (7.999)
Observations	292	289	281	289
R-squared	0.367	0.346	0.414	0.407

To evaluate the impact of reflection exercises on the student’s performance, we estimate WLS model (2):

$$Grade_{ij} = Reflection_{ij} + Univ_j + Gender_j + Year_j + GPA_j + AcctFinMajor_j + Transfer_j + WorkHrs_j + StudyHrs_j + HW_{ij} + Attendance_{i,j} + i.MaritalStatus_j + \epsilon \quad (2)$$

Reflection is an indicator equal to 1 for students in the experimental group who participated in the reflection activity. The remaining control variables are as described in Model (1).

The results, presented in Table 3, examine the effects of reflection on Exam 2 (Column 1), Exam 3 (Column 2), and final course grades (Column 3). We find that the reflection activity has a positive and statistically significant impact on the Exam 2 and Exam 3 scores, as indicated by the statistically significant positive coefficient on *Reflection*. Consistent with the baseline regression presented in Table 2, we observe a significant and negative coefficient on *University* for Exam 2 and the final grade. Additionally, GPA and attendance remain strong positive predictors of performance. The remaining relations align with the patterns observed in our baseline analysis.

Table 3
Reflection Regression Results

Regression results from WLS regressions using Model (2) testing the effectiveness of the reflection exercise in improving student scores. *Reflection* is an indicator equal to 1 when the student is in the reflection experimental group and has participated in the reflection activity. All control variables from Table 2 are utilized in the regressions. In the first column, the dependent variable is the second exam grade, the second column uses the third exam grade as the dependent variable and the last column has the final course grade as the dependent variable. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) E2	(2) E3	(3) Course Grade
Reflection	9.064** (3.693)	7.725* (4.198)	0.160 (2.033)
Control Variables	YES	YES	YES
Observations	284	280	289
R-squared	0.363	0.411	0.407

Table 4 examines whether the effect of the reflection exercise differs by student performance, focusing on students in the lower quartile of prior performance. Lower-performing students may face greater difficulty adjusting study strategies or may engage less seriously with reflection activities, while higher-performing students may have less scope for improvement. Alternatively, reflection may be particularly beneficial for lower-performing students if it encourages more effective study behaviors. To test for differential effects, we interact the reflection indicator with an indicator for students in the bottom quartile of the prior performance distribution.

The results provide limited evidence of heterogeneity in the effect of reflection. The interaction between reflection and lower-quartile status is not statistically significant for Exam 2 or for final course outcomes, including the final course grade and course pass rates. While the interaction term is positive and statistically significant for Exam 3 and the Exam 3 pass indicator, this effect does not persist across earlier exams or translate into differences in overall course performance. Taken together, these findings suggest that the impact of reflection does not differ systematically across student performance groups and is not concentrated among lower-performing students.

Table 4
Reflection Effects by Prior Performance: Lower-Quartile Students

Table 4 reports regression results examining whether the effect of the exam reflection exercise varies by prior student performance. The dependent variables are Exam 2, Exam 3, and the final course grade, as well as indicators for passing the exam or course, where applicable. Continuous outcomes are estimated using weighted least squares regressions, and pass outcomes are estimated using logit models. Reflection is an indicator equal to one for students assigned to the reflection experimental group who participated in the reflection activity. Lower Quartile is an indicator equal to one if the student's prior performance falls in the bottom quartile of the relevant score distribution. Interaction terms between Reflection and Lower Quartile capture whether the effect of reflection differs for lower-performing students. All specifications include the same set of control variables used in Table 2. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) E2	(2) E2 Pass	(3) E3	(4) E3 Pass	(5) Final Grade	(6) Course Pass
Reflection x Lower Quartile	-0.674 (0.729)	0.961 (0.397)	4.837** (0.040)	2.352** (0.010)	3.730 (0.108)	1.522 (0.279)
Reflection	-5.467*** (0.009)	-4.983*** (0.002)	-0.442 (0.856)	0.557 (0.583)	-0.935 (0.699)	-2.018 (0.228)
Lower Quartile	-19.084*** (0.000)	-6.696*** (0.000)	-24.999*** (0.000)	-5.994*** (0.000)	-14.322*** (0.000)	-4.632*** (0.000)
Control Variables	YES	YES	YES	YES	YES	YES
Observations	299	287	291	287	293	287
R-squared	0.818		0.745		0.555	

Additionally, as discussed in our Methodology section, we explored potential proxies for measuring reflection quality. While our results were inconclusive and thus not reported, we identified a promising correlation: students who provided more extensive written responses to open-ended questions, particularly those about their class experience, tended to perform better on exams. Specifically, students who wrote more when asked about what they liked about the class had higher exam scores. However, further research is needed to definitively establish this connection and to develop reliable measures of reflection quality in the context of finance education.

Discussion

The results highlight that while structured reflection is positively associated with subsequent exam performance, the estimated effects are not uniform across all outcomes or student subgroups. Such non-uniformity is common in educational interventions, particularly in analytical courses where performance reflects both prior preparation and evolving study behaviors. Importantly, statistically significant coefficients should be interpreted in context rather than in isolation. For example, the changing sign on the university indicator across exams likely reflects structural differences in course sequencing and assessment design rather than differences in student ability. Similarly, the negative association between self-reported study hours and exam performance likely captures reactive or inefficient study behavior rather than a causal effect of effort itself.

From a pedagogical perspective, these findings remain directly relevant to AACSB expectations regarding active student engagement and higher-order learning. Structured exam

reflection promotes metacognitive monitoring and behavioral adjustment, aligning with AACSB's emphasis on learning processes rather than rote content mastery. At the same time, the results underscore the need for improved measurement of reflection quality. While word counts and self-reported indicators provide suggestive evidence, future research should develop more direct measures of reflection quality, such as content analysis of written reflections, to better understand how reflection translates into improved performance in analytical disciplines.

Conclusion

We provide evidence that structured exam reflection can enhance student performance in introductory finance courses. Our findings suggest that students who engage in structured reflection experience improved performance on subsequent exams. Additionally, students expressed, both verbally and in course evaluations, that they valued the reflection questionnaires, interpreting them as a sign of the instructor's commitment to their learning and success. This illustrates an additional benefit of incorporating reflection into finance education.

Our study is the first to examine the impact of structured reflection in finance courses, offering a valuable framework for educators seeking to integrate exam reflection into their classrooms. While our findings underscore the benefits of reflection, future research should explore the key determinates of effective reflection and establish measures to assess its quality such as content analysis or linguistic indicators of depth in reflective responses. This would allow educators to optimize the impact of reflection on student learning outcomes.

Finally, our findings align with AACSB guidelines, which emphasize active student engagement and higher-order learning. The AACSB encourages accredited business schools to "facilitate and encourage active student engagement in learning" (AACSB, 2016, p. 30) and to demonstrate "clear evidence of significant active student engagement" (AACSB, 2016, p. 39). By fostering metacognitive thinking through exam reflection, educators can help students develop critical thinking and problem-solving skills that extend beyond the classroom.

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Linking Workplace Ostracism to Job Performance and Exploring the Moderating Effects of Employee Engagement: A Self-Regulation Perspective

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Workplace ostracism is a crucial factor affecting human well-being in organizational settings. Employees who experience exclusion, neglect, and social isolation often suffer from reduced morale and impaired psychological functioning. Based on self-regulation theory, this study examines the direct relationship between workplace ostracism and job performance and investigates the moderating role of employee engagement. Data were collected from 98 full-time employees working in service sector organisations. Confirmatory factor analysis and hypothesis testing were conducted using SmartPLS-4. Results reveal that workplace ostracism is significantly and negatively related to job performance, while employee engagement positively predicts job performance. The findings underscore the importance of cultivating inclusive organisational environments and enhancing engagement mechanisms to safeguard employee productivity and well-being.

Keywords: *Workplace ostracism, employee engagement, job performance, self-regulation, service sector*

Introduction

Workplace ostracism is a pervasive yet often subtle form of interpersonal mistreatment in organisational settings. It is defined as the extent to which an individual perceives being ignored, excluded, or rejected by others at work (Ferris et al., 2008). Unlike overt forms of workplace deviance such as harassment or bullying, ostracism is often ambiguous and difficult to detect, yet its psychological consequences are equally damaging. Employees who experience exclusion through silence, non-recognition, or lack of social interaction frequently suffer from diminished morale, emotional exhaustion, and a weakened sense of belonging. Such experiences challenge fundamental human needs for affiliation and social connection, which are essential for sustained motivation and performance at work.

Existing research indicates that workplace ostracism has serious consequences for both individuals and organizations. Ostracized employees often exhibit reduced job satisfaction, lower

commitment, increased stress, and a higher intention to quit (Williams, 2007; Wu et al., 2012). More critically, ostracism undermines employees' capacity for self-regulation—the psychological process through which individuals control their emotions, thoughts, and behaviors to achieve work goals (Bandura, 1991). When employees are excluded, their cognitive and emotional resources are depleted, leading to impaired work focus, emotional instability, and reduced productivity. From this perspective, ostracism represents a powerful workplace stressor that directly threatens employee effectiveness.

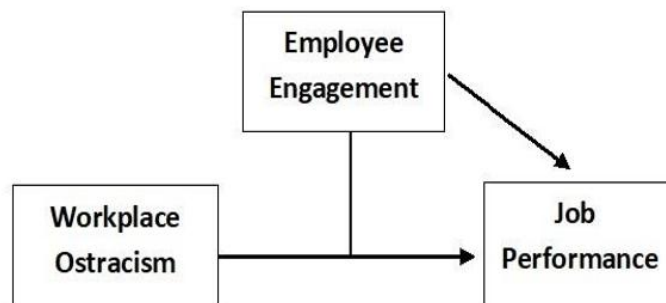
Employee engagement has emerged as one of the most important psychological constructs in understanding work performance. It refers to a positive, fulfilling, and work-related state of mind characterised by vigour, dedication, and absorption (Schaufeli et al., 2002). Highly engaged employees display a strong emotional connection with their jobs, invest substantial energy in their work roles, and consistently demonstrate superior performance. Prior studies show a strong positive association between employee engagement and task performance, organizational citizenship behaviour, and overall effectiveness (Kahn, 1990; Rich et al., 2010). However, despite the well-established positive role of engagement, limited empirical attention has been given to its capacity to offset the harmful effects of negative workplace experiences such as ostracism.

Drawing on **Self-Regulation Theory**, this study proposes that workplace ostracism disrupts employees' internal self-control mechanisms, thereby weakening their motivation and job performance. At the same time, employee engagement may function as an important psychological resource that strengthens individuals' resilience and work involvement. Although some scholars suggest that engagement may buffer the adverse effects of workplace stressors, empirical evidence on its moderating role in the ostracism–performance relationship remains scarce, particularly in service sector contexts of emerging economies.

Therefore, the present study seeks to examine: (i) the direct effect of workplace ostracism on job performance, (ii) the direct effect of employee engagement on job performance, and (iii) the moderating role of employee engagement in the relationship between workplace ostracism and job performance. By integrating self-regulation theory with workplace ostracism and engagement literature, this research contributes to a deeper understanding of how social exclusion influences employee performance and whether engagement can serve as a protective mechanism. The findings offer important theoretical insights and practical implications for organisations seeking to improve employee well-being and sustain productivity in competitive work environments.

Proposed model: Based on the above-mentioned theoretical framework, the following research model is hypothesized:

Figure 1
Conceptual Design of the Study



H1. Workplace ostracism is negatively related to employee job performance.

H2. Employee engagement is positively related to employee job performance.

H3. Employee engagement will moderate the relationship between workplace ostracism and employee job performance.

Literature Review

Self-Regulation Theory

Self-Regulation Theory (SRT) explains how individuals control, monitor, and direct their thoughts, emotions, and behaviours to achieve desired personal and professional goals (Bandura, 1986, 1991). Self-regulation involves processes such as self-monitoring, goal setting, behavioural adjustment, and emotional control. These regulatory mechanisms enable individuals to remain focused, motivated, and productive, especially under stressful conditions. When self-regulatory resources are intact, employees are better equipped to deal with challenges and maintain consistent work performance. However, when these resources are depleted due to stressors, emotional distress, or social exclusion, individuals experience difficulty in sustaining effective work behavior (Vohs & Baumeister, 2004).

From an organizational perspective, self-regulation is critical for sustained job performance because employees are routinely required to manage stress, regulate emotional responses, and maintain motivation under pressure. Experiences of rejection, isolation, or exclusion directly threaten individuals' self-esteem and sense of control, leading to emotional imbalance and reduced work effort. Prior research suggests that social exclusion weakens self-regulation by draining emotional and cognitive resources, thereby impairing attention, decision-making, and task persistence (Baumeister et al., 2002; Williams, 2007). In the workplace context, this depletion process manifests in the form of disengagement, emotional exhaustion, and performance decline.

In the context of this study, self-regulation theory provides a robust framework to explain how workplace ostracism disrupts an employee's psychological equilibrium, weakens motivation, and ultimately reduces job performance. At the same time, employee engagement may function as a compensatory psychological resource that strengthens individuals' regulatory capacity and promotes sustained work involvement.

Workplace Ostracism and Job Performance

Workplace ostracism refers to the extent to which employees perceive that they are ignored, excluded, or treated as socially invisible by coworkers or supervisors (Ferris et al., 2008). Unlike overt mistreatment, ostracism is subtle and ambiguous, yet its psychological impact is often more damaging because it threatens fundamental human needs of belongingness, self-worth, and meaningful existence (Williams, 2007). Ostracised employees frequently experience anxiety, emotional distress, and cognitive withdrawal, which directly interfere with their ability to perform effectively at work.

Empirical evidence consistently demonstrates a negative relationship between workplace ostracism and job performance. Leung et al. (2011) found that ostracism in service organisations significantly reduced task performance and increased turnover intention. Similarly, Balliet and Ferris (2013) showed that ostracised employees engage in lower prosocial behaviour and exhibit diminished cooperative performance. From a self-regulation standpoint, exclusion disrupts employees' internal control processes, resulting in emotional instability, reduced goal orientation, and impaired concentration on work tasks.

Furthermore, ostracism induces emotional exhaustion and stress, which further weaken employees' ability to sustain work effort over time (Ferris et al., 2008). Prolonged exposure to workplace exclusion may lead employees to disengage psychologically from their roles, reduce discretionary effort, and display counterproductive work behaviours. Based on these theoretical and empirical arguments, it is expected that workplace ostracism will significantly and negatively affect job performance.

Hypothesis 1 (H1): Workplace ostracism is negatively related to job performance.

Employee Engagement and Job Performance

Employee engagement is defined as a positive, fulfilling work-related state characterised by Vigor, dedication, and absorption (Schaufeli et al., 2002). Engaged employees invest their physical, cognitive, and emotional energies into their work roles and display sustained enthusiasm, persistence, and involvement in job tasks. Engagement has been recognised as a central driver of individual and organisational performance outcomes.

A substantial body of research has established a strong positive relationship between employee engagement and job performance. Kahn (1990) argued that engaged employees express themselves physically, cognitively, and emotionally during role performance, leading to higher effectiveness. Rich et al. (2010) empirically confirmed that engagement significantly predicts task performance and organisational citizenship behaviour. Highly engaged employees demonstrate stronger work focus, superior problem-solving ability, and greater resilience under pressure.

From a self-regulation perspective, employee engagement represents a powerful psychological resource that enhances employees' capacity to manage stress and sustain motivation. Engaged employees possess higher levels of intrinsic motivation and are better equipped to regulate negative emotions and maintain performance under adverse conditions. Therefore, it is expected that employee engagement will positively influence job performance.

Hypothesis 2 (H2): Employee engagement is positively related to job performance.

Moderating Role of Employee Engagement

Although workplace ostracism is inherently damaging, employees differ in how they respond to exclusion. Psychological resources such as engagement may help employees withstand the harmful impact of workplace stressors. Engaged employees often exhibit higher emotional stability, stronger work identity, and greater persistence, which may enable them to buffer the negative effects of ostracism.

Previous studies suggest that engagement can reduce the impact of adverse workplace conditions on performance and well-being (Fleck & Inceoglu, 2010). Engaged employees tend to remain psychologically connected to their work even in unfavourable social environments. Accordingly, it is theoretically plausible that employee engagement may weaken the negative relationship between workplace ostracism and job performance by strengthening self-regulation and motivational resources.

However, empirical evidence on this moderating role remains limited and inconsistent. While some studies suggest buffering effects, others indicate that the damage caused by social exclusion may be too strong to be neutralised by motivational states alone. Therefore, this study empirically

examines whether employee engagement moderates the relationship between workplace ostracism and job performance.

Hypothesis 3 (H3): Employee engagement moderates the relationship between workplace ostracism and job performance.

Methodology

Sample and Procedure

A cross-sectional survey design was adopted for this study. A total of 150 full-time service sector employees were contacted via email. After screening for incomplete responses, 98 valid questionnaires were retained for analysis. Participants were assured of anonymity and confidentiality to minimise response bias. Data were analysed using IBM SPSS 22 and Smart PLS-4.

Measures

- **Workplace Ostracism:** Measured using a ten-item scale by Ferris et al. (2008). Cronbach's $\alpha = 0.72$.
- **Employee Engagement:** Measured using ten items from Shuck et al. (2017). Cronbach's $\alpha = 0.72$.
- **Job Performance:** Measured using sixteen items from Koopmans (2014). Cronbach's $\alpha = 0.83$.

All items were measured on a five-point Likert scale.

Common Method Bias

As all data were self-reported, the possibility of common method bias exists. To mitigate this risk, respondents were assured of anonymity, and Harman's single-factor test was conducted. Results indicated that no single factor dominated the variance, suggesting that common method bias was not a major concern.

Measurement

Measurement Model

Confirmatory factor analysis using Smart PLS-4 established acceptable convergent and discriminant validity. All factor loadings exceeded 0.70, Cronbach's alpha and composite reliability (CR) values were above 0.70, and average variance extracted (AVE) exceeded 0.50. Discriminant validity was confirmed through the HTMT ratio (<0.90).

Hypothesis Testing

- **H1:** Workplace ostracism negatively predicted job performance ($\beta = -0.540$, $p < .001$).
- **H2:** Employee engagement positively predicted job performance ($\beta = 0.437$, $p < .001$).
- **H3:** The interaction between workplace ostracism and employee engagement was not significant ($\beta = 0.209$, $p > .05$).

Thus, **H1 and H2 were supported**, while **H3 was rejected**.

Control variables (age, tenure, and gender) were tested and found to be non-significant.

Results

Confirmatory Factor Analysis

A confirmatory factor analysis was conducted using SmartPLS-4 to determine the concurrent validity of the drawn construct. As a part of the measurement model evaluation, constructs with low factor loadings were excluded (<0.600) (Gefen & Straub, 2005). Only Factors with above factor loading (>0.700) were considered in the factor structure.

To test the reliability of the constructs, this study used Cronbach's alpha and composite reliability (CR). Cronbach's alpha value of each construct exceeded the 0.700 threshold. All the CR values were higher than the recommended value of 0.700 (Wasko & Faraj, 2005). The convergent validity of the construct was accepted, considering the average variance extracted (AVE) was over 0.500. The results of the reliability and validity of the construct are shown in Table 1.

Table 1
Results of Convergent Validity

Constructs	Items	Loadings	Cronbach Alpha	rhoA	CR	AVE
Workplace Ostracism	WPO3	0.756	0.878	0.881	0.878	0.644
	WPO4	0.847				
	WPO6	0.844				
	WPO7	0.759				
Employee Engagement	ENG5	0.858	0.862	0.868	0.862	0.677
	ENG6	0.738				
	ENG10	0.867				
Job Performance	JP7	0.805	0.895	0.900	0.896	0.633
	JP9	0.808				
	JP11	0.719				
	JP12	0.747				
	JP16	0.889				

Discriminant validity was assessed by the heterotrait-monotrait (HTMT) ratio of correlations. The square root of AVE for the construct was more significant than inter inter-construct correlation. With values below the threshold of 0.900, discriminant validity was established. The results of the discriminant analysis are shown in Table 2.

Table 2
Results of Discriminant Analysis (HTMT Ratio)

	1	2	3
1. Workplace Ostracism	0.714		
2. Employee Engagement		0.840	
3. Job Performance			0.825

Testing of Hypothesis

First, the impact of workplace ostracism on employees' job performance was studied. Second, the impact of employee engagement on the job performance of the individuals was studied, and finally, the moderating effect of employee engagement was tested on the relationship between workplace ostracism and job performance. Path Analysis was carried out to determine the proposed relationships in the Model.

Effect of Workplace Ostracism on Job Performance (testing of H1)

Workplace Ostracism was found to have a negative and significant correlation with Job Performance ($\beta = -0.540$, $\text{Adj.}R^2 = 0.581$, $p < 0.000$). It is confirmed that Workplace Ostracism emerged as a strong predictor of Job Performance within an organisational setup. The More ostracism employees experienced, the more likely it was that they would produce relatively poor job performance. The $\text{Adj.}R^2$ 0.581 values confirmed workplace ostracism significantly predicts 58.1 per cent variation in job performance; therefore, H1 was confirmed. The outcomes are shown in Table 3.

Effect of Employee Engagement on Job Performance (testing of H2)

Employee Engagement was found to have a Positive and significant correlation with Job Performance ($\text{Std.}\beta = -0.437$, $p < 0.000$, $\text{Adj.}R^2 = 0.677$), indicating that individuals who felt more involved were more likely to create superior job performance. The $\text{Adj.}R^2$ 0.677 values confirm employees' engagement significantly predicts 67.7 per cent variation in job performance within the service sector; therefore, H2 was confirmed. The outcomes are shown in Table 3.

Testing the Moderating Effect of Workplace Ostracism and Employee Engagement on Job Performance (testing of H3)

Confirmation on moderating properties of the Interaction variable (WPO*EE) was conducted by application of moderation analysis. It can be observed that these variables accounted for an insignificant amount of variation in the Employees' Job Performance ($\text{Std.}\beta = 0.209$, $p < 0.003$, $\text{Adj.}R^2 = 0.727$). Results indicate that there is no significant moderation between WPO and EE on employee job performance; therefore, H3 was rejected. The outcomes are shown in Table 3.

Table 3
Results of Hypothesis Testing

Hypothesis	Path	Std. β	t-value	p-value	Result
H1	WPO \rightarrow JP	-0.540	6.11	< 0.001	Supported
H2	EE \rightarrow JP	0.437	4.92	< 0.001	Supported
H3	WPO \times EE \rightarrow JP	0.209	1.31	> 0.05	Not Supported

Note: WPO= Workplace Ostracism, EE= Employee Engagement, JP= Job Performance

Discussion

Theoretical Implications

The findings confirm that workplace ostracism is a strong negative predictor of job performance. Consistent with self-regulation theory, ostracised employees experience emotional exhaustion and reduced psychological resources, which diminish their capacity to perform effectively. Employee engagement was found to be a robust positive predictor of job performance; however, it did not significantly moderate the ostracism–performance relationship.

These results suggest that while engagement improves performance directly, it cannot fully offset the psychological harm caused by exclusion. Ostracism exerts a deeply disruptive influence that may overpower the motivational benefits of engagement alone.

Managerial Implications

The findings of this study offer important implications for managers and organisations operating in service-based environments. First, the strong negative effect of workplace ostracism on job performance highlights the urgent need for organizations to actively prevent exclusionary behaviours. Managers should promote inclusive workplace cultures through clear communication norms, team-based work structures, and zero-tolerance policies against social exclusion. Regular sensitivity training and leadership development programs can help supervisors recognise and intervene in early signs of ostracism.

Second, although employee engagement was found to significantly enhance job performance, it did not significantly buffer the negative effects of workplace ostracism. This indicates that organizations cannot rely on engagement initiatives alone to counteract the damage caused by social exclusion. Instead, engagement strategies such as recognition programs, participative decision-making, and meaningful job design should be implemented alongside strong anti-ostracism policies.

Finally, organisations should establish confidential grievance redressal systems and psychological support mechanisms to protect employees experiencing exclusion. By proactively addressing workplace ostracism and simultaneously strengthening employee engagement, organisations can improve performance, well-being, and long-term workforce sustainability.

Limitations

The study relied on self-reported, cross-sectional data from a single sector, limiting generalizability and causal inference. Future studies should employ longitudinal and multi-source data, include additional control variables, and explore mediating psychological mechanisms.

Conclusion

The self-regulation theory emphasizes the importance of social context and social support in the workplace. Individuals who feel connected and valued in the workplace tend to have better job performance, while ostracism may weaken this connection and lead to adverse outcomes. Similar studies have portrayed an inverse relationship between ostracism at the workplace and the outputs of employees (Lee & Allen, 2002). This study not only intends towards the influence of workplace ostracism and employee productivity but also determines how employee engagement plays a moderating role in the relationship between workplace ostracism and the work output of human resources. The critical aspects of the current study are mentioned below. First, when employees become the victim of ostracism in their work environment, their productivity is subject to a gradual downward shift. Second, employee engagement-related interventions facilitate the job performance of individuals. Well-engaged employees are always healthy contributors as their engagement leverages their productivity. Finally, it was found that employee engagement-related initiatives and interventions are potential tools for countering the ill effects of workplace ostracism on the job performance of the workforce, but not to a

significant extent. Human resources with a higher level of engagement in the organizational work environment may reduce instances of suffering resulting from workplace ostracism via effective engagement, along with strengthening employee self-regulation mechanisms.

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Appendix A: Measurement Items

All constructs were measured using previously validated scales and assessed on a **five-point Likert scale** ranging from **1 = Strongly Disagree** to **5 = Strongly Agree**.

Workplace Ostracism Scale

(Ferris et al., 2008)

1. Others ignored me at work.
2. Others left the area when I entered.
3. My greetings have gone unanswered at work.
4. Others avoided talking to me at work.
5. Others treated me as if I were invisible.
6. I was excluded from work-related social gatherings.
7. Others acted as if they did not care about me.
8. I felt left out of conversations at work.
9. Others refused to acknowledge my presence.
10. I was intentionally excluded by coworkers.

Employee Engagement Scale

(Shuck et al., 2017)

1. I feel a strong sense of belonging to my job.
2. I am enthusiastic about my work.
3. I am deeply involved in my job.
4. I feel energized when I am working.
5. I am rarely distracted when I am working.
6. I am committed to giving my best effort at work.
7. I feel motivated to go beyond what is expected of me.
8. My job inspires me.
9. I am fully absorbed in my work activities.
10. I take pride in the work that I do.

Job Performance Scale

(Koopmans, 2014)

1. I manage to plan my work so that it is done on time.
2. I keep in mind the results that I have to achieve in my work.
3. I can separate main issues from side issues at work.
4. I can perform my work efficiently.
5. I take on challenging tasks when they are available.
6. I am proactive in accomplishing my duties.
7. I perform well in my assigned responsibilities.
8. I complete my work with high quality.
9. I achieve the objectives of my job.
10. I work accurately and thoroughly.

11. I persist in difficult situations at work.
12. I solve problems that arise in my job effectively.
13. I adapt well to changes in my job.
14. I demonstrate professionalism in my work conduct.
15. I consistently meet my work targets.
16. I put in extra effort when necessary to get the job done.

ChatGPT: An Application in Finance Classroom to Teach Programming Skills

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Abstract

This paper presents a teaching project designed to introduce Visual Basic for Applications (VBA) programming in the context of testing market efficiency through technical analysis, targeting professionals with no prior coding experience. To enhance learner engagement and support, ChatGPT is employed as a virtual teaching assistant to explain foundational programming concepts. The replication of the human-generated output using ChatGPT suggests that ChatGPT can assist in generating simple code snippets, though it falls short in handling more complex programming tasks. These findings highlight the importance of understanding fundamental programming structures and logic to use artificial intelligence (AI) tools effectively. The project also establishes a foundation for the future development of more advanced financial planning and analysis (FP&A) applications.

Keywords: Artificial intelligence, ChatGPT, Excel, VBA, technical analysis

Introduction

The weak-form efficient market hypothesis states that technical analysis strategies based solely on past stock prices are not consistently profitable (Fama, 1998). Nevertheless, empirical evidence of market anomalies challenges this view. For example, Sim and Kim (2022) show that an enhanced momentum strategy, grounded in salience theory, outperforms the traditional momentum strategy. Similarly, Lee et al. (2022) find that portfolios based on momentum perform better than those based on analyst recommendations. While such strategies may tempt investors to trade frequently, research shows that most trading approaches underperform over time—especially after accounting for transaction costs (Barber & Odean, 2000).

Against this backdrop, we present a teaching project that introduces Visual Basic for Applications (VBA) programming through technical analysis, requiring no prior coding experience. To enhance engagement, we employ ChatGPT as a virtual teaching assistant to introduce foundational programming concepts. The project covers key programming elements and

Excel-specific features, including variables, loops, conditionals, cell references, form controls, and error handling. While the project can be done in standard spreadsheets, we offer a more visually appealing alternative through the use of UserForms with graphical interfaces. The end-user enters the buy and sell signals and clicks on the Run button to calculate the strategy return along with the benchmark buy-and-hold return.

This project provides a practical and engaging framework for revisiting technical analysis and market efficiency, making it particularly suitable for classroom use. Moreover, it serves as a cautionary tool for novice investors who may be misled by technical trading strategies often promoted in financial media. We advocate that investors experiment with such models in simulated environments before risking real capital.

Finally, our findings suggest that while ChatGPT can be a helpful tool for learning and assisting with basic programming tasks, its output is often inaccurate and unreliable for more complex challenges. This is consistent with Tian et al. (2023), who note that although Artificial Intelligence (AI) tools like ChatGPT can manage standard coding problems, their effectiveness declines as task complexity increases. These limitations underscore the importance of learning coding fundamentals—not only to better understand the underlying logic but also to use AI tools more efficiently and effectively.

The structure of this paper is as follows: The next section reviews the use of ChatGPT in the field of education and briefly surveys the literature in technical analysis. We then introduce the data used for the VBA program. Next, we present the VBA code and its corresponding output, followed by an attempt to replicate these results using ChatGPT, with a subsequent comparison of the outcomes. Finally, we conclude with a discussion of the implications for instructors and address the limitations of the current study.

Background

ChatGPT in Education: Opportunities and Limitations

Developed by OpenAI and powered by natural language processing (NLP), ChatGPT can perform a wide range of tasks, including code generation, text composition, image creation, and question answering. The integration of large language models (LLMs) such as ChatGPT into education has generated growing interest, particularly for their potential to support both instructors and students in technical disciplines. Lo et al. (2023) provide a broad discussion on data science, AI, and financial markets. Lo (2023) reviews the literature of ChatGPT on education and finds that ChatGPT can generate course syllabi and provide teaching suggestions without the need for major changes. Pedagogically, successful integration of ChatGPT requires thoughtful curriculum design. Choi (2023) advocates for case-based analysis rather than simple recall tasks, promoting critical thinking and responsible use of AI. Cotton et al. (2024) and Perkins (2023) recommend that instructors validate all AI-generated references and outputs to avoid misinformation. Additionally, the inability of standard plagiarism software to detect ChatGPT-generated content raises concerns about academic integrity (Khalil & Er, 2023; Opara et al., 2023). Mills et al. (2025) emphasize the need for teacher training and curriculum alignment, especially when teaching computational thinking outside of computer science programs. For students, ChatGPT enhances engagement by offering automated feedback, helping articulate coding goals in plain language, and generating working code—especially beneficial for non-programmers such as finance professionals learning

VBA. Javaid et al. (2023) identify dozens of classroom applications, including content summarization, writing support, and logic enhancement.

Beyond utility, ChatGPT may also contribute to deeper learning. Garcia (2025) finds that students using ChatGPT engage more in reflection about the logic and function of code. Park and Kim (2025) report that ChatGPT users outperform peers relying on traditional platforms like Stack Overflow. Shethiya (2025) adds that tools such as GitHub Copilot help streamline code generation and bug detection, further supporting problem-solving skills. Bray (2025) shows how natural language programming can be highly effective for teaching finance professionals VBA. This approach reduces entry barriers and helps connect financial logic with programming syntax.

However, ChatGPT has limitations such as accuracy, and its performance varies significantly across disciplines. Multiple studies warn of ChatGPT's tendency to produce hallucinated citations, factual errors, and vague responses, particularly when prompts are imprecise (Baidoo-Anu & Ansah, 2023; Hu, 2025). These limitations can hinder critical thinking and lead to misunderstanding in technical subjects (Cambaz & Zhang, 2024). Poldrack et al. (2023) show that such issues persist even in GPT-4. Furthermore, Newton and Xiromeriti (2023) report high performance in economics but less consistency in fields like medicine and physics. Moreover, Hender (2023) highlights that AI-generated code often lacks contextual robustness and may fail tests without careful human validation. In programming education, these issues are especially relevant for novice learners who may overly rely on AI-generated outputs.

Taken together, LLMs like ChatGPT offer substantial value as instructional aids—particularly for non-CS learners. For finance professionals learning VBA, AI-assisted tools can lower technical barriers, promote experimentation, and personalize learning. However, these benefits must be balanced with careful instructional design, guided use, and awareness of the technology's limitations. This study contributes to the growing conversation by applying these insights in a finance-specific programming context, using ChatGPT to enhance the learning of VBA through both pedagogical innovation and practical implementation.

Weak-Form Market Efficiency

Technical analysis is a security analysis methodology for forecasting future financial price movements based on an examination of past market data, primarily price and volume data. It employs a wide variety of charts that show price and volume movements over time. Technical analysis applies to any tradable securities, such as stocks, options, commodities, currencies, futures, and indices.

Whenever the stock market has a bull run for an extended period of time, journalists, along with commentators, start discussing a looming correction (Harring, 2023). These arguments find support in academic literature. For example, De Bondt and Thaler (1985) rank stocks on three to five-year returns and find that past winners tend to be future losers, and vice versa. They attribute these long-term return reversals to investor overreaction to past information, which links to the behavioral decision theory of Kahneman and Tversky (1979). It seems that many investors adopt a profit-taking strategy, that is, to sell off after a price run-up. This behavior aligns with the widely promoted investment principle of “buy low, sell high” (BLSH), which is frequently endorsed in financial media and investment newsletters (Kee, 2013)

There are numerous variations of the BLSH. The most frequently cited one is probably the Dow Theory, a market timing strategy (bull vs. bear) developed by Charles Dow more than 100 years ago. It suggests that the market is predictable through technical analysis. Cowles (1933)

analyzes trading based on the Dow Theory from December 1903 to December 1929. Specifically, Cowles derived bullish, bearish, and neutral signals from Hamilton's editorials. If bullish, Cowles assumed a long position, 50% in the stocks comprising the Dow Industrial Index and 50% in those comprising the Dow Transportation Index. Cowles assumed a short position for bearish signals and invested in a riskless asset with a neutral signal. In terms of performance, Cowles documented an annualized return of 12% from the Dow trading strategy. Similarly, Brown et al. (1998) find that strategies based on the Dow Theory generated positive risk-adjusted returns, high Sharpe ratios, and positive alphas.

Although technical indicators or oscillators, such as the Moving Average Convergence Divergence (MACD) indicators, are available through various financial websites (e.g., Yahoo Finance) and widely used among traders and practitioners, there is limited discussion of them in the academic literature, especially in mainstream finance textbooks (Appel, 2003). The weak-form market efficiency theory dispels the use of technical analysis because the past price data are publicly available. The Dow theorists and chartists also acknowledge the informational efficiency of the stock market. This raises an important question: why do we study technical analysis if it has no predictive power of future price movements? The answer lies in human behavior and the "irrational exuberance" of individual investors. According to Hamilton (2006), who elucidates the basic outlines of the Dow Theory, "Prosperity will drive men to excess, and repentance for the consequence of those excesses will produce a corresponding depression." Such behavioral biases are often not fully or rationally incorporated into market prices, potentially creating opportunities for abnormal returns. However, most mainstream finance textbooks provide limited discussion or empirical support for this perspective.

Although this paper does not develop a program to model the effects of behavioral biases on investor returns, it contributes to the literature by engaging students in technical analysis through hands-on projects. It encourages critical thinking about market efficiency by introducing a simplified BLSH strategy based solely on the magnitude of the S&P 500 index pops and drops. Students are allowed to construct technical indicators, test trading strategies, and explore the limitations and possibilities of technical analysis in the context of both market theory and investor behavior.

Data

We retrieve daily stock trading data for three index funds: SPDR S&P 500 (SPY), iShares MSCI Emerging Markets (EEM), and iShares U.S. Real Estate (IYR) from their inception dates to July 15, 2014, using data from Yahoo Finance. A sufficiently long period after 2014 is reserved for testing the out-of-sample performance of BLSH strategies. To implement the BLSH strategy, we define critical "dip" and "pop" points that trigger buy and sell decisions, respectively. Five hundred random combinations of buy and sell signals are generated using thresholds between 1% and 5% for sell signals and between -1% and -5% for buy signals. Our strategy executes trades intraday upon signal generation, rather than waiting until the next trading day. Given the availability of high-frequency, near real-time data, immediate execution is appropriate; the closing prices of liquid index funds are unlikely to experience material last-minute volatility.

Results

This section presents the results of the data analysis. First, we examine the performance of the BLSH strategy based on the data described in the previous sections. Following this, the process of creating an interactive BLSH UserForm using VBA code is introduced. Subsequently, we prompt ChatGPT to generate and optimize the coding. Finally, the human-generated code is compared with the code produced by ChatGPT, highlighting the implications for instructors in terms of effectiveness, reliability, and the potential integration of AI-assisted programming tools in education.

Human Output

BLSH Strategy Results

Table 1 summarizes the results from the 500 random sample strategies generated by Listing 7 in the Appendix. The analysis reveals that, on average, there are no statistically significant differences between the returns of the SPDR S&P 500 ETF (SPY) and the benchmark returns, nor between the returns of iShares MSCI Emerging Markets ETF (EEM) and their respective benchmarks when we use t-statistics. Although the return differential between iShares U.S. Real Estate (IYR) and its benchmark is positive and statistically significant, the result is only marginally significant at the 10% level. These findings align with the weak-form efficient market hypothesis, which posits that technical analysis, such as BLSH strategies, is unlikely to consistently outperform market returns. Moreover, our use of unadjusted closing prices for the benchmark means the buy-and-hold return is likely understated, as it does not account for the reinvestment of dividends.

The main purpose of the paper is to teach basic VBA programming skills to enable finance professionals to conduct and possibly automate financial analyses with the help of modern AI tools such as ChatGPT. Although a full test of BLSH trading strategies is beyond the scope of this paper, recent empirical research documents that while technical analysis may offer some short-term predictive value, there is no consistent evidence supporting its long-term profitability (Neely, 2003; Park & Irwin, 2010). The potential reasons for the lack of outperformance may be random fluctuations in stock prices that are not driven by fundamental news (Wu et al., 2022), heterogeneous investor beliefs (Hillenbrand & McCarthy, 2025), and irrational investors' herding behaviors (Christie & Huang, 1995; Spyrou, 2013), among other factors.

Table 1
BLSH Strategy

We test the BLSH strategy on three index funds: SPDR S&P 500 (SPY), iShares MSCI Emerging Markets (EEM), and iShares U.S. Real Estate (IYR) from the inception dates to July 15, 2014. We use close prices without dividend adjustments. To implement the BLSH strategy, we use combinations of dip and pop critical points that trigger buy or sell decisions. For example, if the market price of SPY dips by 2%, it is classified as a buy decision under the 2% threshold. Similarly, if the price pops by 3%, it is classified as a sell decision under the 1% threshold, but not under the 4% threshold. Five hundred random combinations of buy and sell signals are generated using thresholds between 1% and 5% for sell signals and between -1% and -5% for buy signals. Reported returns are in percentages.

Ticker	Benchmark Return	BLSH Strategy				
		N	Mean Return	Min Return	Max Return	Stdev
SPY	348.89	500	272.86	-24.82	1,060.40	289.63
EEM	371.54	500	577.65	14.86	2,111.29	440.68
IYR	108.00	500	601.94*	130.28	1,517.75	309.02

* represents significance at the 10% level.

A Simple Interactive UserForm: VBA Implementation of the BLSH Strategy

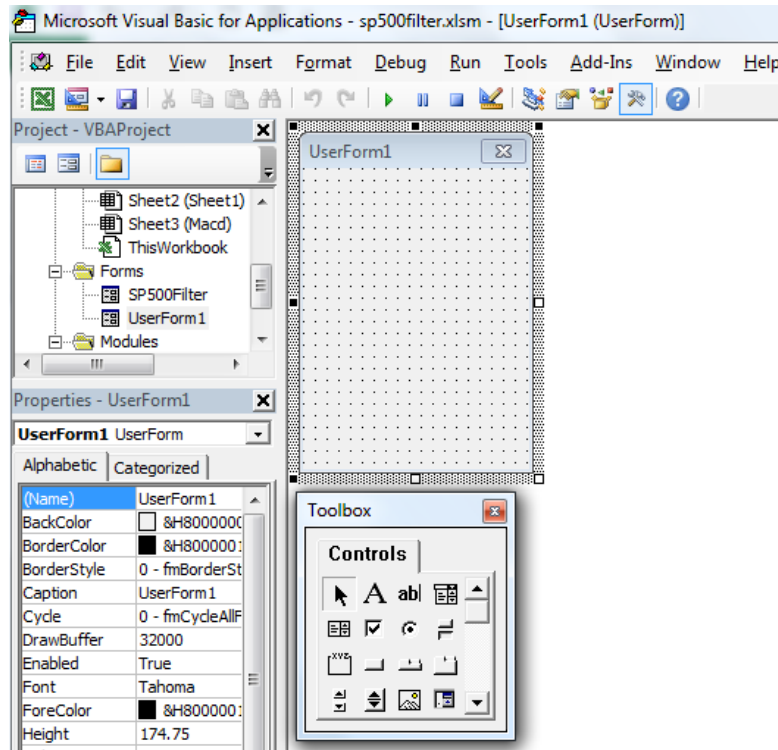
This section describes how to create a simple interactive BLSH UserForm. A UserForm is a user-friendly customized interface developed in VBA to interact with users and to make data entry easier and controllable. Figure 1 presents an example of the UserForms created in the study. We divide the process of creating this simple UserForm into four steps and describe each step in detail below.

Figure 1
The BLSH UserForm

Step 1: Design the UserForm Layout and Add Controls

To open the Visual Basic (VB) editor, click on the Microsoft Excel Developer tab. To add the Developer tab, click on File, Options, Customize Ribbon, and check the Developer checkbox. Then click on Visual Basic, which is the first item on the left of the ribbon. Next, click Insert, UserForm. Figure 2 presents a newly created UserForm, Properties Window, Toolbox, and the Project Explorer. The UserForm has a dotted border. The grid of dots on the form helps align items. The UserForm can be resized by dragging the small white squares on the border, in the lower-right corner, and halfway along the bottom and right sides of the form. With the UserForm selected, type “SP500Filter” in the Name property. This is typically the first item on the list in the Properties Window. Then, change the Caption property to “S&P 500 Filter,” which immediately shows on the “Title” bar of the form. When naming the form and its controls, users must not include spaces in the name or use any VBA reserved words, such as “Date.”

Figure 2
Project Explorer, Properties Window, Toolbox, and a Newly Created UserForm



Next, add controls to the UserForm. The controls are items, such as labels, textboxes, and command buttons, that will be placed on the form. The standard selection of controls is represented by buttons on the Toolbox.

Add labels: To add the form name “S&P 500 Filter,” simply drag the Label icon “A” from the Toolbox onto the UserForm and then insert the text by double-clicking the newly created label. Similarly, add the “Buy Signal,” “Sell Signal,” “Strategy Return,” “Benchmark Return,” and the four “%” labels.

Add textboxes: To add a textbox next to the “Buy Signal” label, drag the TextBox icon “ab” to the right of the “Buy Signal” label. Similarly, add the remaining three textboxes.

Add command buttons: Drag the Command Button icon to the UserForm to create a command button. Repeat three times to create three command buttons.

It is good practice to rename controls to improve code readability and clarity for users. Names are used in the Excel VBA code. Captions are those that appear on the screen. Click on each control and change the name and caption of the control in the Properties Window, following Table 2.

Table 2
Names and Captions of the Controls

Control	Name	Caption
UserForm	SP500Filter	S&P 500 Filter
Text Box	BuyBox	
Text Box	SellBox	

Text Box	StrategyReturnBox	
Text Box	BenchmarkReturnBox	
Command Button	Run	Run
Command Button	Reset	Reset
Command Button	Cancel	Cancel

Step 2: Show the UserForm

The UserForm can be shown manually or automatically. To show the UserForm manually on the spreadsheet, click the Developer tab and insert a Button (Form Control). Form Controls are objects that can be placed on a Worksheet or UserForm to enable interactive functionality. Attach the macro named Filter_Setup, located in the workbook sp500_yahoo.xlsm (sp500_yahoo.xlsm!Filter_Setup), to the Button just created, which corresponds to the subroutine presented in Listing 1.

Listing 1: SP500 Filter Setup and Display

```
Sub Filter_Setup()  
SP500Filter.Show  
End Sub
```

Default values for the buy and sell signals on the UserForm are filled by the subroutine UserForm_Initialize, and it is automatically executed when the Show method is called. In the Project Explorer window, right-click on SP500Filter and then click View Code. Choose UserForm from the left drop-down list and Initialize from the right drop-down list. Add code lines as in Listing 2.

Listing 2: Default Initialization of UserForm Fields

```
Private Sub UserForm_Initialize()  
'Empty NameTextBox  
BuyBox.Value = -1.5  
SellBox.Value = 1.5  
StrategyReturnBox.Value = ""  
BenchmarkReturnBox.Value = ""  
End Sub
```

Step 3: Coding the Command Buttons on the UserForm

Although the UserForm created above looks neat already, nothing will happen when we click the command buttons on the UserForm. We then add procedures to the three command buttons to activate the UserForm's functionality. For teaching purposes, the coding process is illustrated below in detail.

Coding the Run button: In the Project Explorer, double-click on SP500Filter and then double-click on the Run button on the UserForm. Listing 3 shows the coding for the Run subroutine, which calculates the strategy return and updates the text box when the Run button is clicked.

Listing 3: Coding the Run button

```

Private Sub Run_Click()
  Dim Lastrow As Integer, Position As Integer, i As Integer, j As Integer, TotalReturn As Double
  TotalReturn = 1#: Position = 0
  'Check user inputs and initialize variables
  If BuyBox.Value >= 0 Or SellBox.Value <= 0 Then Call MsgBox
  With Sheets("SP500")
    Lastrow = .Cells(Rows.Count, 1).End(xlUp).Row
    'Main calculations: With a buy signal, set Position=1. With a sell signal, update
    TotalReturn and set Position=0.
    For i = 3 To Lastrow
      If (.Cells(i, 2) / .Cells(i - 1, 2) - 1) * 100 <= BuyBox.Value * 1# And Position = 0 Then
        Position = i
      If (.Cells(i, 2) / .Cells(i - 1, 2) - 1) * 100 >= SellBox.Value * 1# And Position > 0 Then
        TotalReturn = TotalReturn * .Cells(i, 2) / .Cells(Position, 2): Position = 0
      End If
    Next i
    'If Position = 0 at the end, close the position. Then output values to the UserForm.
    If Position > 0 Then TotalReturn = TotalReturn * .Cells(Lastrow, 2) / .Cells(Position, 2)
    StrategyReturnBox.Value = (TotalReturn - 1#) * 100
    BenchmarkReturnBox.Value = (.Cells(Lastrow, 2) / .Cells(2, 2) - 1) * 100
  End With
End Sub

```

Next, a line-by-line explanation of the Run_Click() subroutine is provided. Lines 1 and 20 mark the beginning and the end of the subroutine. Access to a procedure can be controlled by an access level specified by a private or public keyword. A private procedure can be called by other procedures within the same module, but not by procedures of outside modules. In addition, its name does not appear in the Macros dialog box. A public procedure can be called by procedures of the same module and by procedures of other modules. It can also be accessed through the Macros dialog box, as its name appears there. If a block of code is only used in a certain form, then make it private. However, if the same code must be shared across multiple forms, then put that code in a module and make it public so all forms in the program can access it.

Line 2 declares variables, which provide the ability to store something in them so that the content of the variables can be used or changed later in the procedure. Variables represent a powerful feature of programming languages. The simplest way to declare a variable in a procedure is to use the Dim statement. Variables *Lastrow*, *Position*, *i*, and *j* are declared as integers with allowable range from -32,768 to 32,767, and *TotalReturn* as a double with allowable range from -1.79769313486232E308 to -4.94065645841247E-324 for negative values and

4.94065645841247E-324 to 1.79769313486232E308 for positive values. VB editor will set aside sufficient memory for an integer variable (2 bytes) and a double variable (8 bytes).

Line 3 assigns initial values to variables. To store a value in the memory reserved for a variable, type the name of the variable, followed by the assignment operator, which is =, followed by the value you want to store. For example, `TotalReturn = 1#` statement assigns 1.0 to TotalReturn, and the # sign indicates a double data type. The colon separates statements on the same line. Although in many situations it can make the code difficult to read or debug, there are instances (like initializations in Listing 3) that would make for cleaner reading, rather than introducing some many lines.

Line 4 is a comment that is preceded by the apostrophe (') sign. Comments are marked green in the VB editor. Lines 8 and 15 are also comment statements.

Lines 5 and 10 to 13 represent conditional statements that execute a group of statements, depending on the value of an expression. The typical structure is `If ... Then ... Else ... End If`. As in Line 5, the `If` statement uses a single-line syntax because of short and simple tests. If anything other than a comment appears after `Then` on the same line, the statement is treated as a single-line `If` statement. The `If` statement in Line 11 uses multiple-line syntax, which provides more structure and flexibility and is usually easier to read, maintain, and debug. VB editor first evaluates the condition. If the condition is True, the statements following `Then` are executed. If the condition is False, each `ElseIf` statement (if there are any) is evaluated in order. If no `ElseIf` condition evaluates to True, or if there are no `ElseIf` statements, the statements following `Else` are executed. The `Then` keyword is optional, and the `End If` keyword terminates the `If...Then...Else` block.

The `Call MsgBox` in Line 5 calls a Sub procedure `MsgBox`. Although the block of code in the `MsgBox` procedure can be included inside the `Run_Click` subroutine, using a separate Sub procedure makes the program easier to understand and debug. Another advantage is that the `MsgBox` Sub can be called from other procedures as well.

Another key VBA concept is how to correctly reference worksheets and cells. Line 6 specifies the worksheet to work with where Line 7 refers to cells on the worksheet. One can refer to a particular cell as `Cells(row,column)`. The `Cells` property works well for looping through a range of cells, because one can substitute variables for the index numbers. In *Listing 3*, `Cells(i, 2)` refers to the i^{th} row and the 2^{nd} column. Alternatively, one can use the alphabet in the column index. `Cells(2, 2)` is the same as `Cells(2, "B")`. The statement `.Cells(Rows.Count, 1).End(xlUp).Row` deserves further explanation because it is a common method for locating the last nonblank cell in a column. In VBA, the `With` statement is often used to specify the object context for subsequent lines of code. For example, if `With Worksheets("SP500")` is used, then a line like `.Cells(i, 1)` refers specifically to a cell in the SP500 worksheet. The dot (.) before `Cells` is essential—it tells VBA to apply the reference within the `With` block's specified object. If the dot is omitted and you simply write `Cells(i, 1)`, VBA will reference the active worksheet instead, which may not be the intended one. This can lead to incorrect results or errors if the wrong worksheet is active during code execution. `Cells(.Rows.Count, 1)` is the very last cell at the bottom of column A. `Cells(.Rows.Count, 1).End(xlUp)` performs the equivalent of pressing `End`, and then the up arrow key in that cell. This moves us up to the last non-blank cell in column A. The `.Row` returns the row number of the last non-blank cell in column A.

Lines 9 to 14 check for buy and sell signals and carry out calculations accordingly through a loop statement, which enables performing the same task repeatedly. The loop can be implemented using several methods, such as the `For` loop, the `Do While` loop, and the `Do Until` loop. *Listing 3* uses the `For ... Next` loop with a default step size of 1 that sets the variable `i` to have the values 3,

4, 5, ..., Lastrow, and for each of these values, runs through the VBA code inside the loop. Alternatively, a step size can be specified. Sometimes it is necessary to use the Exit For statement to jump out of the loop and continue with the next line of code outside the loop.

Listing 4: Coding the Reset button

```
Private Sub Reset_Click()  
Call UserForm_Initialize  
End Sub
```

Listing 5: Coding the Cancel button

```
Private Sub Cancel_Click()  
Unload Me  
End Sub
```

Coding the Reset button: In the Project Explorer, double-click on SP500Filter and then double-click on the Reset button on the UserForm. Add coding *Listing 4* to the Sub routine.

Coding the Cancel button: In the Project Explorer, double-click on SP500Filter to open the associated UserForm. Then double-click the Cancel button within the UserForm. Add coding *Listing 5* to the Sub routine that closes the UserForm when the Cancel button is clicked.

Error handler: When users click on the Run button, we check the user inputs for buy and sell signals to ensure the idea of buy on dip and sell on pop. We require that BuyBox.Value < 0 and SellBox.Value > 0. Otherwise, we ask the user to either cancel the trial or re-input the signals. Add the code in *Listing 6* to implement the error handler.

Listing 6: Error handler

```
'Error handler  
Sub MessBox()  
Dim iRet As Integer  
Dim strPrompt As String  
Dim strTitle As String  
' Prompt  
strPrompt = "Check your input to ensure:" & vbNewLine & "Buy signal < 0 and Sell  
signal > 0!"  
' Dialog's Title  
strTitle = "Buy on dip & Sell on pop"  
'Display MessageBox  
iRet = MsgBox(strPrompt, vbRetryCancel, strTitle)  
  
' Check pressed button  
If iRet = vbCancel Then  
    Unload SP500Filter  
    Exit Sub  
Else
```

```
Unload SP500Filter  
SP500Filter.Show  
End If  
End Sub
```

Step 4: Test the UserForm

Exit the VB editor. Download the S&P 500 historical price from Yahoo Finance and keep the date and adjusted close price columns only. Sort the data by ascending date. Finally, the designed S&P filter can be tested out.

The Appendix demonstrates a VBA simulation that generates the results in Table 1. From a simulation of 500 runs, we find that most BLSH strategies fail to deliver superior returns relative to a simple buy-and-hold strategy. These results support the weak-form efficient market hypothesis as described in the BLSH Strategy Results section.

ChatGPT Output

In this section, we replicate the program developed manually by leveraging ChatGPT.

Step 1: Design the UserForm Layout and Add Controls

In the VB editor, a set of commands to perform a specific task is placed into a procedure, which can be a function or a Sub. While a function returns a result, a subroutine does not. Figure 3(a) shows a ChatGPT-generated explanation of functions vs. subs on March 8, 2023. The same prompt was resubmitted on May 13, 2025, with the updated output shown in Figure 3(b). The newer version includes clearer visual cues and more practical examples, reflecting the tool's ongoing improvement. As AI capabilities continue to evolve, business professionals with basic coding skills will be better positioned to leverage these tools for solving problems more efficiently. The VB editor recognizes a Sub because the commands are positioned between the start and end commands, Sub and End Sub, respectively.

Figure 3 An Explanation of Function vs. Sub by ChatGPT

(a) ChatGPT Output on 3/8/2023

B What's the difference between functions and sub

In VBA, a function is a piece of code that performs a specific task and returns a value to the calling procedure, while a sub (short for subroutine) is a piece of code that performs a specific task but does not return a value to the calling procedure.

A function can be called from within a formula in a worksheet cell, or from another procedure in VBA. When a function is called, it performs its task and then returns a value back to the calling procedure, which can then use that value as needed.

A sub, on the other hand, is typically called from another procedure in VBA. It performs its task, but does not return a value to the calling procedure. Instead, it may modify the contents of the worksheet, display a message to the user, or perform other actions.

Here's an example of a function and a sub:

```

vbnet
Function MyFunction(x As Integer, y As Integer) As Integer
    MyFunction = x + y
End Function

Sub MySub(x As Integer, y As Integer)
    MsgBox "The sum of " & x & " and " & y & " is " & (x + y)
End Sub
    
```

In this example, the function `MyFunction` takes two integer arguments `x` and `y`, adds them together, and returns the result. The sub `MySub` takes the same arguments, but instead of returning a value, it displays a message box to the user with the sum of the two values.

(b) ChatGPT Output on 5/13/2025

regenerate based on this prompt:

Sure! Here's a regenerated explanation based on your prompt "What's the difference between functions and sub" in VBA:

What's the Difference Between Functions and Subroutines in VBA?

In VBA (Visual Basic for Applications), **functions** and **subroutines** (commonly referred to as "subs") are both blocks of reusable code, but they serve different purposes:

- A **function** is designed to **perform a task and return a value** to the calling code.
- A **sub** is designed to **perform a task without returning a value**.

Key Differences

Feature	Function	Subroutine (Sub)
Returns a Value	Yes	No
Used in Formulas	Yes (can be called in worksheet cells)	No
Called by Code	Yes	Yes
Typical Use	Calculations, data processing	Showing messages, updating worksheets

Example

```

vbnet
Function AddNumbers(x As Integer, y As Integer) As Integer
    AddNumbers = x + y
End Function

Sub ShowSum(x As Integer, y As Integer)
    MsgBox "The sum of " & x & " and " & y & " is " & (x + y)
End Sub
    
```

- `AddNumbers` is a **function**: it takes two numbers and **returns their sum**.
- `ShowSum` is a **subroutine**: it takes the same inputs but instead of returning the result, it **displays it in a message box**.

When to Use What?

- Use a **function** when you need to calculate and use a result.
- Use a **sub** when you want to perform an action (e.g., display output, modify a worksheet) without returning data.

Figure 4 Display a UserForm using ChatGPT

B write a sub to show userform SP500Filter

Assuming that you have already created a userform named "SP500Filter", you can use the following VBA code to show the userform:

```
vbnet Copy code  
  
Sub ShowSP500Filter()  
    SP500Filter.Show  
End Sub
```

In this code, the sub `ShowSP500Filter` simply calls the `Show` method of the `SP500Filter` userform object. This will display the userform to the user when the sub is executed.

You can call this sub from a button click event or from another procedure in your VBA code. For example, if you wanted to show the userform when the workbook is opened, you could add the following code to the `Workbook_Open` event handler:

```
vbnet Copy code  
  
Private Sub Workbook_Open()  
    ShowSP500Filter  
End Sub
```

This will automatically display the userform when the workbook is opened.

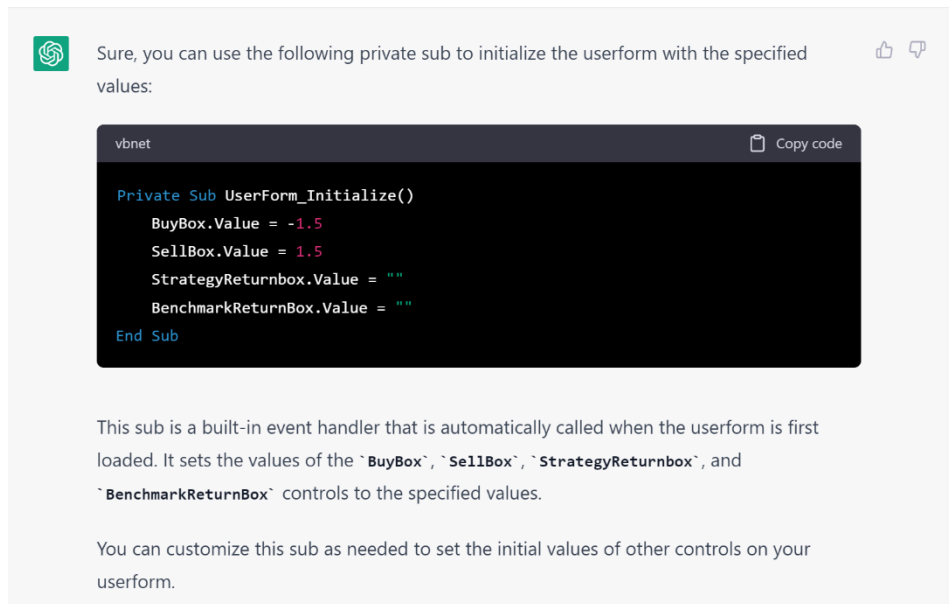
Step 2: Show the UserForm

Figure 4 shows ChatGPT's version of displaying the UserForm "SP500Filter." ChatGPT produced three functional lines of code that successfully display the UserForm. For this relatively simple task, the model completed the assignment correctly without requiring further prompt refinement or manual adjustments.

Figure 5 shows the ChatGPT version of UserForm initialization. The number of lines of code increases to six. We can see it is similar to Listing 2. Therefore, ChatGPT serves as an assistant to help write simple programs based on our prompts.

Figure 5 Initialize the UserForm using ChatGPT

B write a private sub to initialize the userform with the following: BuyBox.Value = -1.5
SellBox.Value = 1.5
StrategyReturnbox.Value = ""
BenchmarkReturnBox.Value = ""



Sure, you can use the following private sub to initialize the userform with the specified values:

```
vbnet Copy code  
Private Sub UserForm_Initialize()  
    BuyBox.Value = -1.5  
    SellBox.Value = 1.5  
    StrategyReturnbox.Value = ""  
    BenchmarkReturnBox.Value = ""  
End Sub
```

This sub is a built-in event handler that is automatically called when the userform is first loaded. It sets the values of the `BuyBox`, `SellBox`, `StrategyReturnbox`, and `BenchmarkReturnBox` controls to the specified values.

You can customize this sub as needed to set the initial values of other controls on your userform.

Steps 3 and 4: Coding the Command Buttons on the UserForm and Testing the UserForm

When requesting code outputs from ChatGPT, longer versions often result in fragmented responses. Since the generated code is not fully functional on its own, testing becomes infeasible without adjustments. However, with basic coding knowledge, these outputs can be refined to work properly. Despite these limitations, ChatGPT remains a valuable tool for finance professionals and instructors, offering significant potential to enhance productivity and streamline coding tasks.

Comparison

The analysis reveals that ChatGPT provides programming examples accompanied by clear explanations and valuable resources on various topics, all of which can significantly enhance the learning reinforcement process. However, there are certain limitations in its performance, particularly when tasked with more complex coding assignments. While ChatGPT can successfully generate relatively simple code, it encounters difficulties when asked to implement more intricate functions. For instance, ChatGPT successfully completed steps 1 and 2, but when we requested ChatGPT to generate the simulation code presented in the Appendix, it consistently failed to produce the complete program. It stopped midway through the coding process, even after multiple attempts to prompt it to continue. We then instructed ChatGPT to generate the first 50 lines of code before continuing, yet it remained unresponsive to the word count or line number requests. This issue highlights a significant limitation of ChatGPT, particularly when tasked with generating lengthy pieces of code. These observations align with previous research indicating that while

ChatGPT excels at handling simple tasks, it struggles with more complex assignments, often producing incomplete, inaccurate, or unreliable code (Bucaioni et al., 2024; Kuhail et al., 2024; Sergeyuk et al., 2025).

In online forums, users complain about incomplete coding written by ChatGPT. Advanced users may be able to refine prompts for better results. Nevertheless, a basic understanding of coding language and structure is highly beneficial for effective prompt engineering. Therefore, we recommend that finance professionals invest time in acquiring fundamental coding knowledge to use AI tools more effectively and to identify and correct errors when they occur.

Conclusion

This paper presents a simple program that an instructor can develop for classroom use, evaluating whether ChatGPT can assist instructors in achieving their instructional objectives. As an example, it builds an interactive UserForm to implement the BLSH strategy. The discussion covers both basic concepts, such as variable definitions, arrays, functions vs. subroutines, cell and worksheet references, Excel built-in functions, loops, condition statements, and advanced concepts, such as algorithmic simulations step-by-step. These are presented in an easily comprehensible manner.

These findings indicate that ChatGPT can be a valuable tool for assisting instructors in understanding the distinctions between VBA functions and subroutines, as well as in developing code for UserForm. However, when faced with more complex coding requests, ChatGPT encounters challenges, suggesting that while it serves as an effective assistant for generating small code snippets, it cannot fully replace a human coder for more intricate programming tasks. Therefore, teaching core VBA concepts will be helpful for students who wish to build foundational programming skills. Once students have gained this understanding, tools such as ChatGPT can significantly enhance their efficiency in coding tasks, providing valuable support in the development process.

Implications for Instructors

VBA is a powerful tool that instructors can use in the classroom to offer students engaging exercises. We choose VBA for this study because Excel is one of the most accessible and user-friendly programs, making it an ideal platform for learning programming concepts. However, instructors can also consider alternative free programming languages, such as Python or R, for similar educational purposes. By employing a simple and intuitive program that generates numerical examples, students are often more motivated to explore the underlying theories and concepts in greater depth.

This paper introduces one of the most widely used trading strategies in the industry, offering instructors a practical application for teaching. Instructors interested in expanding this approach can adapt the program to implement additional trading strategies, such as momentum trading, position trading, or algorithmic trading. For example, instructors can encourage students to define their own trading rules based on factors like price, trading volume, or time of day. These rules can then be tested, with instructors guiding students to interpret the results and connect them to relevant market theories from the literature.

Our analysis shows that when developing new programs, ChatGPT can serve as a valuable assistant in helping instructors understand and create code. It is also effective in identifying and

correcting mistakes or syntax errors. These findings suggest that even instructors with limited coding experience can leverage ChatGPT to learn programming and develop programs without investing substantial time or effort. However, ChatGPT also struggles to generate complete programs, particularly when dealing with complex functions. While ChatGPT excels at producing simple functions, it faces challenges when tasked with more intricate programming requirements.

Based on these findings, we recommend that instructors plan their coding tasks, breaking them down into smaller and manageable modules. By doing so, instructors can ask ChatGPT to generate code for each module individually and then combine these components to build a complete program.

Limitations and Future Research Topics

This paper focuses on the development of a simple program designed to test the BLSH strategy, the replication of the human-generated output using ChatGPT, and an exploration of practical implications for integrating ChatGPT into classroom instruction. As a way to examine the BLSH strategy, the study employs randomly generated trading signals and t-statistics. This approach is both practical and easy for instructors to implement and straightforward for students to understand, making it particularly well-suited for educational settings.

While more rigorous methodologies for testing market efficiency exist within the finance literature, such approaches are beyond the scope of this paper. Future research may explore the development of more sophisticated programs that implement a wider range of trading strategies, coupled with rigorous testing of theoretical frameworks using advanced statistical methodologies.

With the development of AI technologies, perhaps the future generations of ChatGPT and other generative AI platforms will become more capable of producing code that accomplishes more complex tasks. For instance, the latest Co-Pilot in Excel can already generate trading strategies from instructions. This advancement is already making a tangible impact in real-world education, where AI actively supports instructional design, personalizes learning, and automates technical tasks.

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Appendix

Simulation of the BLSH strategy

Although the interactive UserForm is interesting and easy to operate by users, it can only take one set of initial values at a time. To test out the BLSH strategy, we resort to simulation by drawing random initial values and repeating the process to generate a set of output values. We then analyze these outputs to determine whether the average strategy return differs statistically from the benchmark buy-and-hold return.

Listing 7 shows the VBA code for the simulation. In a nutshell, we perform 500 simulation runs and keep track of the simulation results in a two-dimensional array. Then we calculate the mean, min, max, and standard deviation of the strategy returns across these runs. Some key aspects of the VBA code are explained below.

Two-dimensional array: The array, SR(2 To 501, 6 To 9), has 500 rows and 4 columns. The reason we start with row 2 and column 6 is to make output values to the original spreadsheet easier. For example, we save the first row for headers, and the first 5 columns are already in use. We use columns 6 and 7 to store buy and sell signals, respectively. Column 8 stores the strategy return, and column 9 records the number of transactions.

Random initial values: We limit the random buy signal to a stock price decline from -1% to -5% and the sell signal ranges from 1% to 5%, as specified in the LowerBound and UpperBound. The random initial buy and sell signals are then generated through the built-in RandBetween() function. Once we have the initial signals, strategy returns are calculated using a for loop, as previously described.

Output to worksheet: To improve computational efficiency, simulation results are first stored in the two-dimensional array and then written to the worksheet at the end of the simulation. The code `.Range("F2:I501").Value = SR` writes the SR array to cells F2 through I501 on the designated worksheet. The dot in front of Range refers to the worksheet stated earlier in the code: `With Sheets("SP500")`.

Statistics: Finally, we use built-in functions to calculate the average, minimum, maximum, and standard deviation of these 500 strategy returns.

Listing 7: Simulation of BLSH Strategy

```
Private Sub Random_Click()  
Dim Lastrow As Integer, i As Integer, j As Integer, Position As Integer, count As Integer  
Dim LowerBound As Integer, UpperBound As Integer  
Dim TotalReturn As Double, BuySignal As Double, SellSignal As Double  
'SR is a multidimensional array that stores the buy/sell signals and strategy returns.  
Dim SR(2 To 501, 6 To 9) As Double, Price() As Variant
```

```
With Sheets("SP500")  
  'Initialize variables  
  LowerBound = 10: UpperBound = 50  
  Lastrow = .Cells(Rows.count, 1).End(xlUp).Row  
  'Clear column contents and read price into array  
  .Range("C2:I" & Lastrow).ClearContents  
  .Cells(1, 6).Value = "BuySignal": .Cells(1, 7).Value = "SellSignal"
```

```

.Cells(1, 8) = "Strategy Return": .Cells(1, 9).Value = "# of transactions"

ReDim Price(Lastrow - 1)
Price = Application.Transpose(.Range("B2:B" & Lastrow).Value)
For i = 1 To 500
    'Generate random inputs for the Buy and Sell signals
    BuySignal = -Application.WorksheetFunction.RandBetween(LowerBound,
UpperBound) / 10
    SellSignal = Application.WorksheetFunction.RandBetween(LowerBound,
UpperBound) / 10
    TotalReturn = 1#: Position = 0: count = 0
    'Main calculations: With a buy signal, set Position=1. With a sell signal, update
TotalReturn and set Position=0.
    For j = 2 To Lastrow - 1
        If (Price(j) / Price(j - 1) - 1) * 100 <= BuySignal And Position = 0 Then Position = j:
count = count + 1
        If (Price(j) / Price(j - 1) - 1) * 100 >= SellSignal And Position > 0 Then
            TotalReturn = TotalReturn * Price(j) / Price(Position): Position = 0
        End If
    Next j
    'If Position = 0 at the end, close the position. Then output values to the UserForm.
    If Position > 0 Then TotalReturn = TotalReturn * Price(Lastrow - 1) / Price(Position)
    'output values to the SR array
    SR(i + 1, 6) = BuySignal: SR(i + 1, 7) = SellSignal: SR(i + 1, 8) = (TotalReturn - 1#) * 100:
SR(i + 1, 9) = count
    Next i
    .Range("F2:I501").Value = SR
    'Benchmark Return
    .Cells(1, 10) = "BR": .Cells(2, 10) = (Price(Lastrow - 1) / Price(1) - 1) * 100
    'Simulation Results
    .Cells(1, 11) = "avg_SR": .Cells(1, 12) = "min_SR": .Cells(1, 13) = "max_SR": .Cells(1,
14) = "std_SR"
    .Cells(2, 11) = Application.Average(.Range("H:H")): .Cells(2, 12) =
Application.Min(.Range("H:H"))
    .Cells(2, 13) = Application.Max(.Range("H:H")): .Cells(2, 14) =
Application.StDev(.Range("H:H"))
End With
End Sub

```

Bridging the AI Skill Gap in Finance Education: Bankruptcy Prediction Using ANNs

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AI's transformative impact on finance demands that graduates master both traditional financial principles and advanced AI tools. Teaching AI to students without programming skills presents a significant challenge, as AI fundamentally relies on coding and algorithm development. This gap limits students' ability to fully engage with AI's practical applications, such as data analysis and predictive modeling. This paper introduces an innovative approach to integrating AI into finance education through a hands-on assignment focused on bankruptcy risk prediction using Artificial Neural Networks (ANNs). By replicating previous research using SPSS, a user-friendly statistical software, students engage with AI concepts without requiring extensive coding skills. This method enhances students' understanding of statistical techniques and model evaluation, fostering critical thinking and analytical skills. The assignment includes data collection, variable measurement, and model comparison, providing a comprehensive learning experience. The paper outlines the methods, tools, and impact of this approach, demonstrating its effectiveness in equipping students with practical skills in AI applications within finance. This framework can be adapted for various business contexts, broadening the scope of AI education.

Keywords: Artificial Intelligence, Artificial Neural Networks, Bankruptcy Prediction

Introduction

AI's ability to streamline processes and enhance decision-making has reshaped expectations for finance graduates, who must now master both traditional financial principles and AI tools to drive innovation and efficiency. In response to this growing demand, it is crucial that educational institutions adapt their curricula to prepare students for the AI-driven landscape of modern finance (Wasserman, 2023).

The challenge of teaching AI in business courses, particularly to students without programming skills, lies in the fact that AI, by its very nature, is deeply rooted in coding and algorithm development (Luckin et al., 2016). Without a foundation in programming, students face significant barriers in understanding how AI models are built, trained, and implemented. The true power of AI lies in its application to real-world problems. However, without the ability to write and modify code, students are unable to apply AI to tasks such as data analysis, predictive modeling, or automation. This gap severely limits their ability to utilize AI in meaningful ways, both academically and professionally.

To effectively teach AI to students without coding skills, educators must find ways to bridge this gap, such as using user-friendly AI tools with graphical interfaces, offering supplementary programming instruction, or focusing on conceptual understanding rather than technical implementation. As an example, this paper presents an innovative approach to embedding AI into finance education through a hands-on assignment that focuses on bankruptcy risk prediction using Artificial Neural Networks (ANNs).

The significance of this teaching practice lies in its ability to bridge the gap between theoretical concepts and practical applications, specifically by replicating previous research papers using SPSS in a classroom setting. This approach not only enhances students' statistical skills (data collection, variable measures, sampling, defining models), but also allows them to conduct comparative analysis based on the output generated by SPSS. By doing so, students gain a deeper understanding of AI's application in finance and are better equipped to evaluate and interpret research findings. This practice is particularly valuable for fostering critical thinking and analytical skills, which are essential for success in the finance industry.

We begin by introducing the topic of Bankruptcy Risk and Prediction Methods, outlining the limitations of traditional models and the advantages offered by AI techniques, particularly *Artificial Neural Networks (ANNs)*. The next part, *Application: Bankruptcy Prediction By ANNs*, details the hands-on implementation process. It covers *Data Collection and Preparation*, *Sample Selection*, and the practical use of *SPSS Implementation* to build and evaluate ANN models. Following the technical application, the *Assurance of Learning* section demonstrates how the project aligns with educational standards and learning goals. It outlines the *Grading Rubric*, highlights connections to *AACSB Standard 5: Assurance of Learning*, and discusses *Indirect Measures to Assess and Enhance Student Learning Outcomes*. The *Conclusion* synthesizes the findings and reflects on the broader implications of this pedagogical approach. It includes a *Comparative Discussion*, acknowledges *Limitations and Implementation Challenges*, and highlights the project's value as a *Pedagogical Innovation* in AI-driven finance education.

Bankruptcy Risk and Prediction Methods

Bankruptcy prediction is a critical aspect of financial risk management. Accurate forecasting helps investors, creditors, and regulators make informed decisions and mitigate potential losses. Since the 1960s, traditional models—such as Altman's Z-Score, Beaver's ratios, and logistic regression—have been widely used. These approaches rely on predefined financial ratios and assume linear relationships between variables and outcomes. While they are simple, transparent, and easy to apply, they often oversimplify the complex and dynamic nature of a firm's financial health. Typically, these models are limited to a narrow set of financial indicators and may fail to account for external factors like industry trends or macroeconomic conditions. Moreover, they are static in nature and require manual recalibration to keep up with evolving market environments.

AI seeks to address many of these limitations and significantly enhance predictive accuracy. Traditional models often fall short in capturing the complex, non-linear relationships embedded in financial data. Artificial Neural Networks (ANNs), a key subset of AI, are particularly well-suited to detect and model these intricate patterns—ones that traditional methods might overlook. AI not only improves predictive performance and reduces classification errors (such as false positives and false negatives), but also enables the automated analysis of large datasets, facilitating real-time monitoring and evaluation of numerous firms simultaneously. In recent years, AI and machine learning techniques have emerged as powerful tools for bankruptcy prediction (Shetty et al., 2022;

Hamdi et al., 2024; Letkovský et al., 2024). Among these, ANNs stand out for their resilience and effectiveness, primarily due to their ability to handle non-linear relationships and complex data structures without relying on prior assumptions about data distribution. In this project, our goal is to equip students with a deeper understanding of both the strengths and the challenges associated with applying AI to bankruptcy prediction.

Artificial Neural Networks (ANNs)

In the context of this study, AI refers to computational systems capable of learning patterns from historical data and making predictions on new, unseen data. A key subset of AI is ANNs, which are inspired by the structure and function of biological neural networks. ANNs are widely used in predictive analytics, including financial risk assessment and bankruptcy prediction.

ANNs are computational models that mimic the architecture of the human brain. They consist of layers of interconnected nodes (or neurons) that process input data to generate predictions. ANNs are particularly well-suited for tasks such as bankruptcy prediction because they can learn from data, detect patterns, and make accurate forecasts—even when relationships between variables are complex and non-linear.

An ANN typically includes an input layer that receives data, one or more hidden layers that process the information, and an output layer that produces the prediction. The hidden layers perform a series of calculations, combining the input data with learned weights (synaptic strengths). These weights are adjusted through a learning process called backpropagation, which minimizes the difference between the predicted and actual outcomes.

One of the major advantages of ANNs is their flexibility. Unlike traditional statistical models, ANNs do not require prior assumptions about the distribution of the data. This makes them especially valuable for solving problems involving complex, non-linear relationships. However, designing and configuring ANNs can be challenging—it involves selecting the appropriate network architecture, activation functions, learning algorithms, and other control parameters.

In this project, we focus on two widely used ANN models: the Multilayer Perceptron (MLP) and the Radial Basis Function (RBF) network. These models are not tailored specifically for bankruptcy prediction but serve as general-purpose classification tools adaptable to a range of tasks. The choice of model depends on various factors, including the complexity of the data, the specific nature of the problem, and the desired level of interpretability.

A typical modeling process involves three main steps:

- **Model Building:** The analyst selects a suitable architecture (e.g., MLP or RBF) based on the task and dataset characteristics. This includes defining the number of layers, neurons per layer, activation functions, and other structural elements.
- **Training:** The model is trained using historical (training) data, learning to map input variables (e.g., financial ratios) to the target outcome (e.g., bankruptcy vs. non-bankruptcy). During this phase, the model iteratively adjusts its internal parameters to reduce prediction error.
- **Implementation (Testing & Evaluation):** After training, the model is tested on new data to evaluate its performance. Common evaluation metrics include accuracy, precision, recall, and other relevant indicators to determine which configuration performs best.

While professionals might conduct extensive model selection and tuning, the instructional design of this project prioritizes practical application over exhaustive comparison. Drawing on

previous research using the same dataset, the MLP model has been identified as particularly effective for bankruptcy prediction. To balance conceptual understanding with workload feasibility, students are guided to begin with the MLP model.

Rather than comparing multiple types of models (e.g., MLP vs. RBF), students explore variations within the MLP framework. This includes adjusting parameters such as the number of hidden layers, the number of neurons, learning rates, and combinations of financial indicators. Students then evaluate and compare the performance of these variations using appropriate metrics. This hands-on experimentation helps students understand the influence of model architecture and feature selection on predictive performance while keeping the project scope manageable. We believe this structured, focused approach strikes an effective balance between building conceptual knowledge and fostering practical skills.

Comparative Analysis of Prediction Models

To evaluate the effectiveness of different prediction models, including ANNs, it is essential to perform a comparative analysis. This analysis involves comparing the model's predictions with actual outcomes, which can be visualized using a confusion matrix. The confusion matrix categorizes predictions into four groups: True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN).

- True Positive (TP): When the model correctly predicts a positive class
- False Negative (FN): When the model incorrectly predicts a negative class for a positive instance
- False Positive (FP): When the model incorrectly predicts a positive class for a negative instance
- True Negative (TN): When the model correctly predicts a negative class

In simpler terms, anything "true" means the model was correct, while anything "false" means the model was incorrect. The false positive is sometimes referred to as a Type I error or a false alarm, while the false negative is known as a Type II error.

The effectiveness of a model is typically measured using several key metrics:

Accuracy: The percentage of correctly classified samples, defined as $(TP + TN) / (TP + TN + FP + FN)$. This metric provides an overall measure of the model's performance.

Specificity: The model's ability to correctly identify negative cases (i.e., non-bankrupt firms), defined as $TN / (TN + FP)$. High specificity indicates a low rate of Type I errors (false positives).

Sensitivity: The model's ability to correctly identify positive cases (i.e., bankrupt firms), defined as $TP / (TP + FN)$. High sensitivity indicates a low rate of Type II errors (false negatives).

Precision: The proportion of true positive predictions out of all positive predictions, defined as $TP / (TP + FP)$. High precision indicates that the model is reliable in predicting positive outcomes.

Type I and Type II error rates can also be directly used as metrics to evaluate the prediction models:

- Type I error: $FP / (TP + TN + FP + FN)$
- Type II error: $FN / (TP + TN + FP + FN)$

These metrics are crucial for understanding the performance of AI models in complex applications like bankruptcy prediction.

Application: Bankruptcy Prediction by ANNs

Data Collection and Preparation

The dataset used for this project was obtained from the UC Irvine Machine Learning Repository, a well-known resource for machine learning data. The data, originally collected by the Taiwan Economic Journal, includes financial information from various industries for the years 1999–2009 (<https://archive.ics.uci.edu/dataset/572/taiwanese+bankruptcy+prediction>). The dataset comprises 96 financial ratios and 6,819 observations, of which 220 are bankrupt firms and 6,599 are non-bankrupt firms.

To ensure a robust analysis, the dataset was carefully prepared following the methodologies of previous studies by Brenes et al. (2022) and Liang et al. (2016). This preparation included removing variables with significant outliers and addressing multicollinearity issues, ultimately reducing the number of variables used in the model to 61.

We use this publicly available dataset to ensure that both students and other faculty can directly access and utilize the data for their learning and teaching purposes.

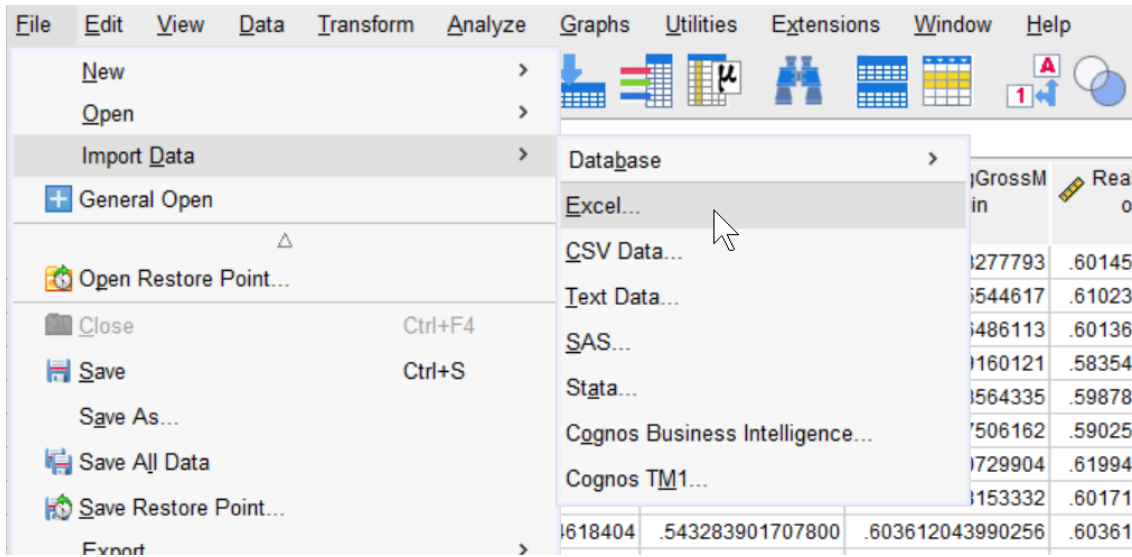
Sample Selection

Given the imbalance between bankrupt and non-bankrupt firms in the dataset, a random subset was selected to create a more balanced sample. Brenes et al. (2022) used a subset with 60% non-bankrupt and 40% bankrupt firms, resulting in a final sample of 550 firms. Liang et al. (2016), on the other hand, used a balanced sample of 239 bankrupt and 239 non-bankrupt firms. These sampling methods were replicated in the classroom assignment to provide students with a realistic experience of data preparation and model development.

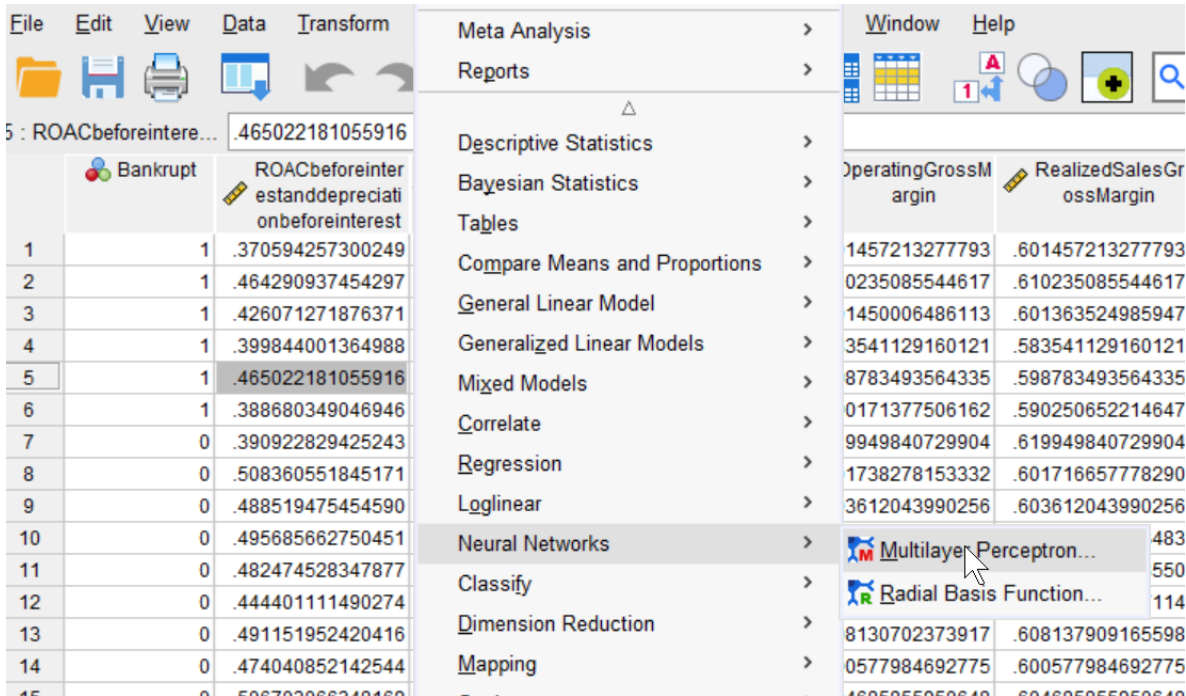
SPSS Implementation

To facilitate the implementation of ANNs, students used SPSS, a user-friendly statistical software. The assignment involved several key steps:

- 1) **Data Import:** Download the data and import the file (CSV or Excel) to SPSS. The data is displayed in the SPSS as in the image below. The task is to predict Bankrupt (output) from the independent variables(inputs).

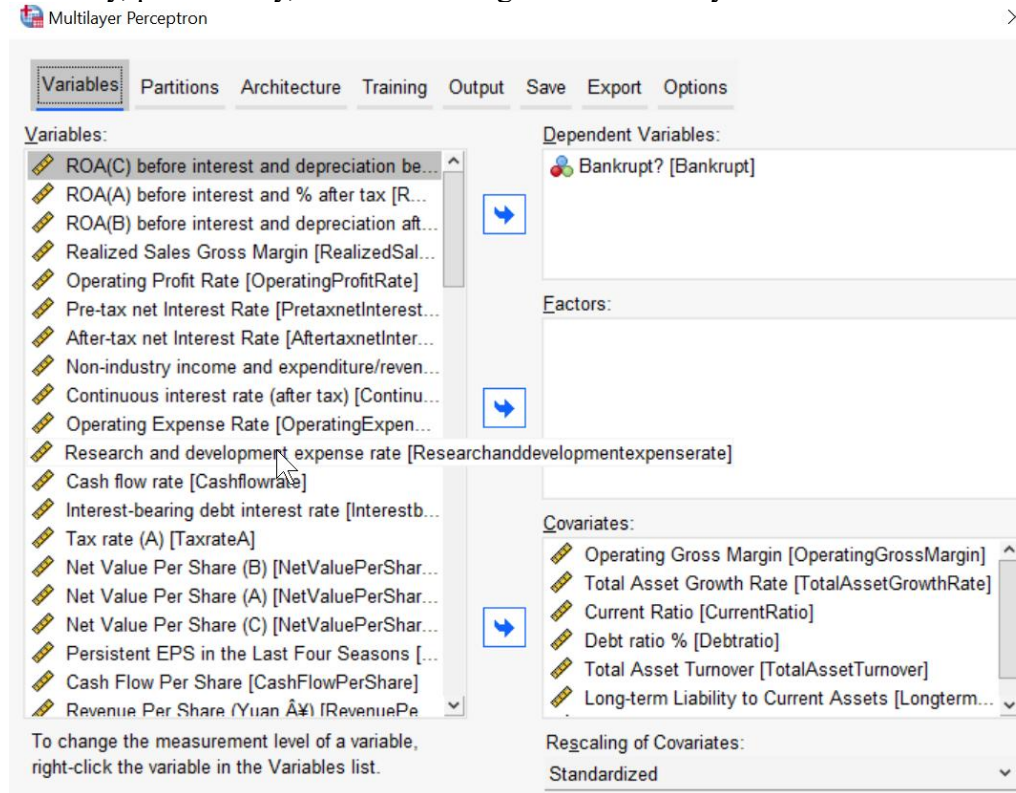


- 2) Model Creation: The Neural Networks (NN) is selected from Analyze tab from the toolbar. Select the Multilayer Perceptron model from the NN option. Multilayer Perceptron (MLP) and Radial Basis Function (RBF) are both types of artificial neural networks, but they differ in their architecture, activation functions, and the way they process information. MLPs are more general-purpose and capable of learning complex, non-linear mappings across the entire input space, while RBF networks are specialized for tasks where the relationship between inputs and outputs is localized and smoother.



- 3) Variable Selection: The independent variable is [Bankrupt?]. Students select independent variables. Their choices should be based on class materials, prior research, and existing

literature. For example, they should consider variables measuring liquidity, long-term solvency, profitability, and asset management efficiency.



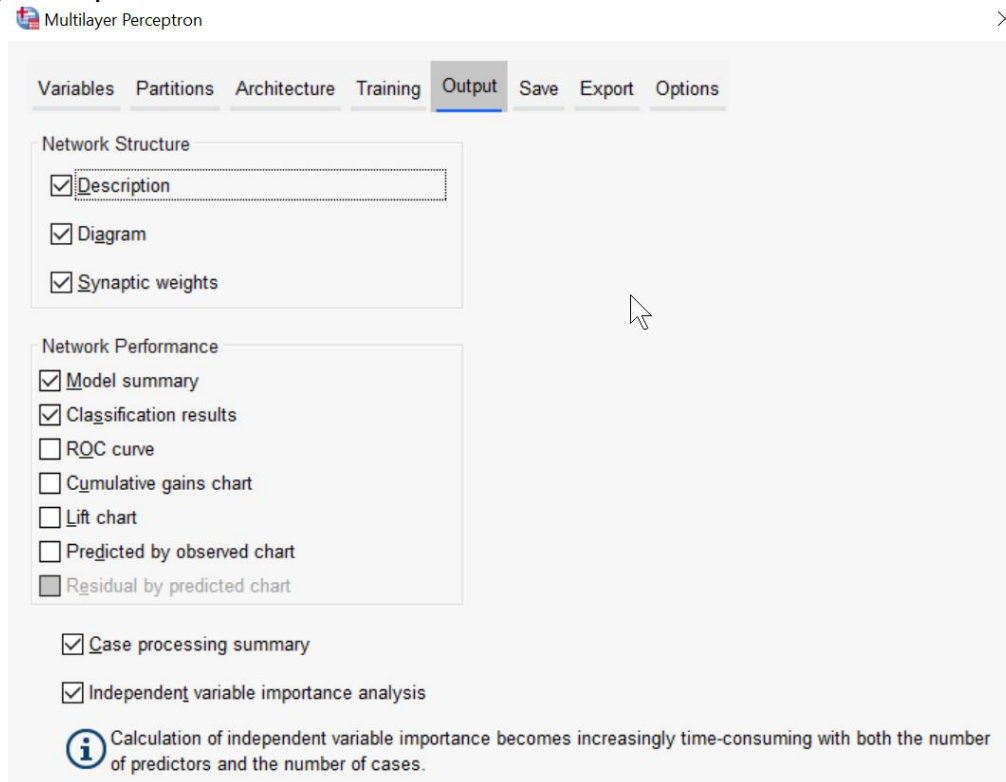
4) Default settings: Leave the default parameters as they are in the following tabs.

Partitions: By default, the sample set is divided into three segments using a random number generator, approximately maintaining a distribution ratio of 70:30:0 for training, testing, and holdout. The training and holdout segments were combined for model creation, referred to as the "training only" set. This larger portion, making up 70% of the dataset, was used for model creation, while the remaining 30% served as the test set. Therefore, the training sample comprises 70% of the final dataset, and the test subset comprises the remaining 30%. The 70/30 split is commonly used in predictive modeling to balance model training and evaluation. 70% of the data is used for training, allowing the model to learn patterns, while 30% is reserved for testing, providing an independent sample to assess generalization. This ratio reduces the risk of overfitting and ensures reliable performance evaluation. It's a widely accepted standard, making it easier to replicate and compare results. While the 70/30 split works well for many scenarios, variations can be used depending on dataset size, with larger datasets sometimes using a 90/10 split or cross-validation for small datasets.

Architecture: The architecture is automatically selected. The layers are generated by the ANN SPSS.

Options: In options tab, we get the option to change the accuracy and training time of the model. By default, the model was trained using a 15-minute session, with the accuracy set to 0.001.

- 5) Output Analysis: The output tab gives options to check the weights assigned by the ANN. Also, the importance of each variable can be seen in the SPSS.



Example 1 SPSS output of one ANN model

Classification

Sample	Observed	Predicted		Percent Correct
		0	1	
Training	0	213	25	89.5%
	1	28	133	82.6%
	Overall Percent	60.4%	39.6%	86.7%
Testing	0	81	11	88.0%
	1	15	44	74.6%
	Overall Percent	63.6%	36.4%	82.8%

Dependent Variable: Bankrupt?

Independent Variable Importance

	Importance	Normalized Importance
Operating Gross Margin	.055	10.9%
Total Asset Growth Rate	.133	26.4%
Current Ratio	.053	10.5%
Debt ratio %	.502	100.0%
Total Asset Turnover	.157	31.2%
Long-term Liability to Current Assets	.031	6.1%
Equity to Liability	.071	14.1%

The classification table summarizes outcomes for both the training and testing datasets, highlighting how well the model distinguishes between bankrupt and non-bankrupt firms. The dependent variable is binary, where 0 indicates a firm is not bankrupt and 1 indicates it is bankrupt.

In the training sample, the model shows strong performance across both categories. It correctly identifies 213 out of 238 non-bankrupt firms (89.5%) and 133 out of 161 bankrupt firms (82.6%). This yields an overall training accuracy of 86.7%, with the correct predictions relatively well-balanced between the two classes (60.4% non-bankrupt, 39.6% bankrupt).

The testing sample further validates the model's generalizability. Out of 92 non-bankrupt firms, 81 are correctly classified (88.0%), and 44 out of 59 bankrupt firms are correctly predicted (74.6%). The overall testing accuracy is 82.8%, indicating good predictive power, especially compared to typical challenges faced in bankruptcy prediction where class imbalance often leads to lower sensitivity for the minority class (usually bankrupt firms).

The second table identifies the most influential financial ratios contributing to the model's predictions. Importance values are presented in both absolute terms and as normalized percentages (where the most important variable is set at 100%). For example, Debt Ratio stands out as the most critical predictor, with a normalized importance of 100%. This highlights that firms with a high proportion of debt relative to assets are more likely to be classified as bankrupt, aligning with financial theory. Total Asset Turnover follows at 31.2%, suggesting that operational efficiency plays a meaningful role in bankruptcy prediction. Total Asset Growth Rate (26.4%) and Equity to Liability (14.1%) also contribute notably to the model's decisions, reflecting the relevance of both growth dynamics and capital structure. Other variables such as Operating Gross Margin (10.9%), Current Ratio (10.5%), and Long-term Liability to Current Assets (6.1%) have lower but still non-trivial importance.

- 6) Comparative Analysis: Repeat the steps described above for two ANN models. Most importantly, conduct a comprehensive comparative analysis of their performance using the previously discussed evaluation metrics: accuracy, specificity, sensitivity (recall), and precision. After calculating and comparing these metrics for both models, analyze the strengths and weaknesses of each model in terms of their predictive power and classification accuracy. Based on the findings, provide a clear recommendation on which model performs better overall and would be more suitable for deployment.

Example 2 Metrics Calculated from SPSS Output

Sample		Classification		
		0	1	Percent Correct
Training	0	213	25	89.5%
	1	28	133	82.6%
	Overall Percent	60.4%	39.6%	86.7%
Testing	0	81 (TP)	11 (FN)	88.04% TP/(TP+FN)
	1	15 (FP)	44 (TN)	74.57% TN/(FP+TN) <= Specificity
	Overall Percent	63.57% (TP+FP)/(TP+FP+TN+FN)	36.42% (FN+TN)/(TP+FP+TN+FN)	82.78% (TP+TN)/(TP+FN+FP+TN) <= Sensitivity

Dependent Variable: Bankrupt?

Average Accuracy	82.78% (TP + TN) / (TP + TN + FP + FN)
Precision	84.38% TP/(TP+FP)
Type I errors	9.93% FP/(TP+TN + FP+ FN)
Type II errors	7.28% FN/(TP+TN +FP+FN)

This table illustrates an example of how to calculate these metrics using values from the SPSS standardized classification table. From this table, we can extract the counts of true positives, true negatives, false positives, and false negatives, which are essential for computing these performance metrics. By using the counts provided in the SPSS classification table, we can plug the values into the relevant formulas and better understand the model's predictive performance.

Assurance of Learning

Grading Rubric

This project was meticulously designed as a dynamic class assignment to rigorously assess individual and team performance. Students were required to download and analyze real-world data, carefully select variables, create representative samples, and develop predictive models, following detailed guidelines provided by the instructor. The assignment fostered critical thinking by requiring students to justify their variable selections and model choices based on class materials, relevant prior research, and the broader academic literature. For example, the students should consider variables measuring liquidity, long-term solvency, profitability, and asset management efficiency, such as Asset Turnover, Debt/Equity, Current Ratio, Quick Ratio, ROA, ROE, and Profit Margin.

The grading rubric for the project report (whether written or presented) includes the following criteria: a clear explanation of the chosen models, accuracy in calculations and analysis, clarity in presenting results (such as tables and charts), correct interpretation of findings, and a discussion of the implications and limitations. The allocation of grading points may vary depending on the students' academic level. This project is designed to be appropriate for senior finance students in

an elective course or for graduate students enrolled in a financial management course. This comparative analysis not only deepens students' understanding of AI's capabilities and limitations in financial applications but also equipped them with the analytical skills essential for success in a rapidly evolving industry.

AACSB Standard 5: Assurance of Learning

Our current grading rubric is intentionally designed to evaluate key learning competency goals directly tied to our graduate program educational objectives and aligned with AACSB Standard 5: Assurance of Learning (AoL). Specifically, we evaluate student performance on the project report—whether submitted in written form or presented orally—that evaluates students based on three key criteria.

The first criterion, model explanation, is linked to *Critical Thinking Skills* competency. Students are expected to articulate a clear and coherent rationale for their selected analytical model, including a thoughtful evaluation of its strengths and limitations, with emphasis on the model's suitability for solving financial problems.

The second criterion, accuracy in calculation and analysis, reflects the *Quantitative and Technical Skills* competency. Hence, students are assessed on their ability to apply ANNs using SPSS in conducting financial predictions, such as bankruptcy forecasting. This includes accurate model development, effective data processing, and sound interpretation of results in addressing complex financial scenarios.

The third criterion, presentation and interpretation of results, corresponds to the *Interpersonal and Team Skills* competency. Students are evaluated on the clarity, organization, and professionalism of their presentation, including the effective use of tables, charts, and visuals. Additionally, they are expected to communicate analytical insights to both technical and non-technical audiences, while actively participating in group discussions and peer feedback sessions.

Indirect Measures to Assess and Enhance Student Learning Outcomes

Student learning outcomes are evaluated through our grading rubric, which is explicitly mapped to the program's competency goals. In addition, we propose using indirect measures—such as student satisfaction surveys—to provide supplementary evidence supporting the effectiveness of this innovative pedagogical approach. Based on our indirect assessment, 81% of students selected 4 out of 5 on the Likert scale—where 4 indicates "Agree"—in response to the question: “*To what extent did using SPSS for model development and data analysis enhance your ability to work with AI-driven financial models?*” A similar proportion of students also selected 4 ("Agree") in response to two additional questions: “*How relevant do you find this project to real-world financial decision-making, such as risk assessment and lending decisions?*” and “*How confident are you in interpreting the SPSS output, including key metrics such as accuracy, sensitivity, specificity, and precision?*” Going forward, we plan to compare learning outcomes between two different cohorts in order to identify any learning gaps. This comparison will inform a "closing-the-loop" action plan aimed at improving the overall project design and enhancing student learning.

Conclusion

Comparative Discussion

AI in finance is commonly taught through either programming-intensive or theoretical approaches. Programming-heavy methods, using tools like Python, R, or MATLAB, offer deep technical immersion by requiring students to build and train machine learning models from scratch. While effective for those with strong coding skills, this approach can pose a steep learning curve for students from non-technical backgrounds, limiting accessibility.

On the other hand, case-based or theoretical courses emphasize literature, conceptual understanding, and real-world applications through discussions and case studies. These help students critically reflect on AI's role in financial decision-making but often lack practical model implementation, reducing hands-on learning opportunities.

Our approach, using SPSS's artificial neural network (ANN) functionality, provides a middle ground. It removes the coding barrier, allowing students to focus on data preparation, model training, evaluation, and financial interpretation. This applied, experiential learning model ensures that students gain practical skills in AI without being hindered by syntax or programming challenges.

In addition to technical proficiency, our method fosters critical thinking, communication, and collaboration through peer feedback and reporting activities. This makes AI education more inclusive and aligned with the real-world demands of financial analytics, while maintaining analytical depth and rigor.

Limitations

Using SPSS instead of direct programming has several limitations. It lacks flexibility and customization compared to Python or R, making advanced modeling and automation more challenging. For example, in this project, students cannot create and customize their SPSS results directly; instead, they must compute comparative metrics based on SPSS output tables. Additionally, SPSS struggles with big data scalability and has fewer machine learning capabilities. However, for this project, SPSS provides sufficient functionality to achieve the intended learning outcomes.

Implementation Challenges

Implementing this project presents several challenges, primarily related to student familiarity with SPSS and maintaining engagement. Since our graduate program focuses on disruptive technology, students are interested in developing quantitative skills and are trained in SPSS from orientation. The curriculum incorporates SPSS projects throughout, ensuring a solid foundation. However, student feedback highlights that lecture notes alone are insufficient for completing the project, suggesting the need for more interactive guidance. Additionally, the project is not well-suited for online or asynchronous courses unless supplemented with detailed instructional videos.

Another challenge arises with students who do not use SPSS in their workplace. While all students in the program have prior SPSS experience, those who do not actively apply it in their jobs reported feeling their skills had become rusty, making it harder to keep up. Addressing these

concerns may involve integrating refresher sessions or providing additional practice exercises to reinforce SPSS proficiency.

Pedagogical Innovation

By leveraging SPSS for data analysis, students are empowered with a user-friendly interface that abstracts away complex coding requirements, allowing them to focus on the critical task of interpreting and comparing results. The consistency and clarity of SPSS's standardized output combined with a structured comparative analysis, enables students to gain a deeper understanding of model performance and effectiveness, fostering a more nuanced grasp of AI techniques in a business context. By adapting this assignment's framework, instructors have the flexibility to incorporate various business datasets, making it possible to teach AI and machine learning concepts across diverse fields such as marketing, operations, and management. This innovative assignment not only broadens the scope of learning but also ensures that students develop versatile skills, positioning them for success in an increasingly AI-driven business environment.

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An Interactive Guide to Equity Index Replications with Financial Market Data

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As equity index-tracking funds are thriving in the financial market, this article provides a step-by-step guide to replicating the price-weighted Dow Jones Industrial Average and the value-weighted Swiss Market Index. Through experiential learning, the interactive Python program guides (i) users to download market data of an index and its constituents, (ii) form an index's replicating portfolio based on its constituents' weights, and (iii) compare the actual index and its replication. The goal is to offer students hands-on experience working with real-world financial data and constructing index-mimicking portfolios. Instructors can adopt this interactive framework to illustrate important finance concepts such as benchmark indices, passive investing, and exchange-traded funds.

Keywords: Index replication, passive investing, exchange-traded funds, financial data, interactive Python, experiential learning

Introduction

Given the growing popularity of equity index-tracking funds (trackers) across international stock markets, this article offers an interactive guide to replicating two real-world equity indices with Python. It aims to provide students with a realistic experience in constructing passive investment products with market data from scratch. In this guide, students will learn how to (i) gather online data on equity indices and their constituents, (ii) aggregate individual stocks into equity indices based on different weighting schemes, and (iii) evaluate the tracking performance of the replicated indices through back-testing. Moreover, students will gain competence in programming and acquire know-how in handling and processing financial data.

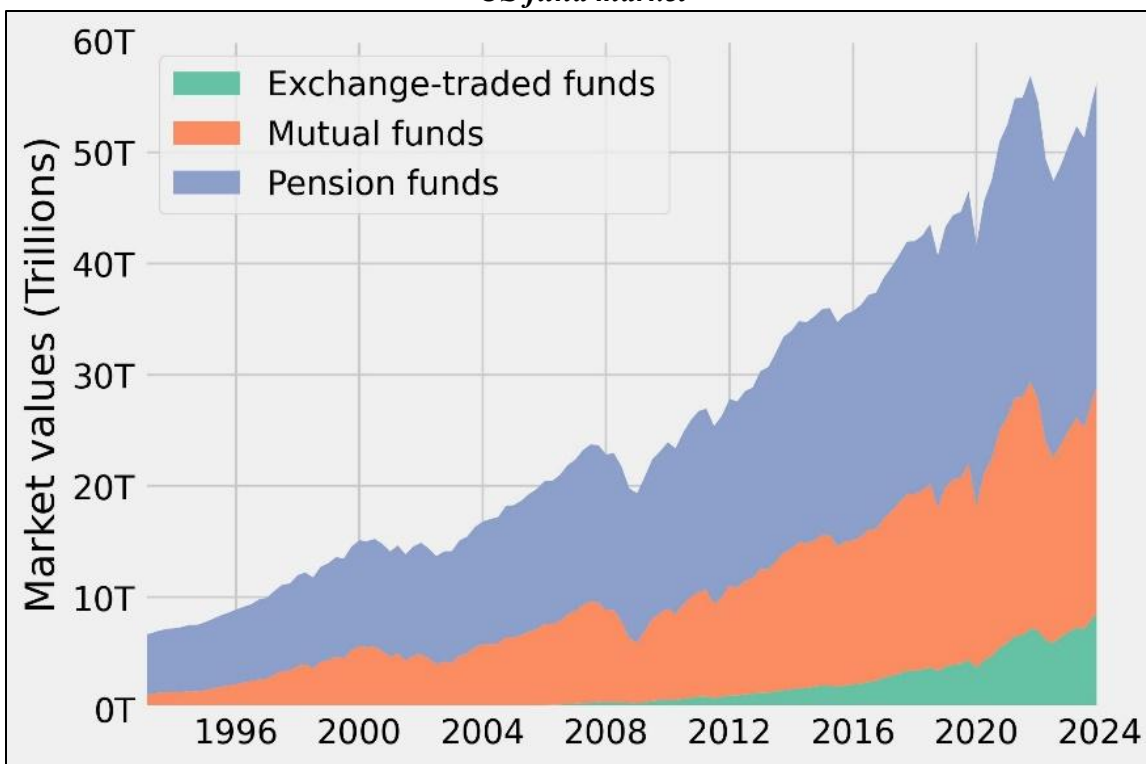
There are ample reasons why passive investing is becoming increasingly popular. In the US stock market, French (2008) reveals that an average investor would gain 0.67% annually by switching to a passive market portfolio from 1980 to 2006. Bessembinder (2018) documents that fewer than 43% of common stocks have higher buy-and-hold returns than the concurrent one-month Treasury bills' returns. Remarkably, he attributes the wealth creation for the US equity market since 1926 to the top 4% performing stocks. Across international stock markets, Bessembinder et al. (2023) find that one-month Treasury bills outperform over 55% of global equities with matched lifetime investment horizons. The contribution of the best 2.4% international stocks generates the entire \$US 75.7 trillion wealth gain in global stock markets from 1990 to 2020.

In other words, one has to be highly skillful (*or lucky*) in stock picking to beat the stock market. By investing in broad market indices, investors are guaranteed not to miss out on the top-performing stocks. Besides, the Capital Asset Pricing Model (Sharpe, 1964) suggests that the market portfolio is the optimal risky portfolio. Any active derivation from the market portfolio leads to under-diversification and a high chance of inferior investment outcome. In practice, a buy-

and-hold strategy in the broad market index proxies for the theoretical market portfolio. The dominance of passive investing applies not only to individual investors but also to professional investors. The influential Carhart (1997) study demonstrates that the active performance of US mutual funds rarely persists over one year. A subsequent study by Choi & Zhao (2021) shows that the one-year mutual fund performance persistence weakens outside the original sample and becomes statistically insignificant from 1994 to 2018. Both studies remind investors to be cautious when relying on professional fund managers to beat the market repeatedly.

An index-tracking fund aims to mimic a benchmark index’s performance, offering investors the returns of a passive buy-and-hold investment strategy. Therefore, investors of index trackers can benefit from risk diversification and exposures to top-performing stocks that drive index movements. Tracker fund managers do not seek to outperform the benchmark. By abstaining fund managers from stock picking or market timing that require constant decision-making and monitoring, management fees of passive tracker funds are lower than their actively managed counterparts. If active portfolio management cannot persistently beat the benchmark, investors are better off investing in passive funds with lower expense ratios for higher after-cost returns. Additionally, the passive buy-and-hold tracking portfolio does not require active rebalancing except for the event of index reconstitution. The lower portfolio turnovers of passive tracker funds entail less capital gain realizations, leading to higher tax efficiency than active funds. Capital gains generated by fund managers from selling capital assets are passed on to fund investors through taxable capital gains distributions (IRS, 2024).

Figure 1
US fund market



Note. The figure shows the quarterly market values of exchange-traded funds, mutual funds, and pension funds in the US from 1993Q1 to 2024Q1. (Data source: Flow of Funds, Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis)

Figure 1 summarizes the quarterly market values of exchange-traded funds (ETFs), open-end mutual funds (MFs), and pension funds (PFs) in the US fund industry from 1993 to 2024. On January 22, 1993, State Street Global Advisors introduced the first US-listed ETF for tracking the performance of the S&P 500 (State Street Global Advisor, 2024). Since then, we have witnessed rapid growth in the market value of the ETF sector, from \$133 million to \$8,841,880 million, a stunning cumulative growth of 66,479.3%. In contrast, cumulative growth rates in the market values of MFs and PFs are merely 16.3% and 4.1%, respectively. According to VettaFi (2024), the top 5 largest US ETFs measured by assets under management (AUM) are all passive index trackers (tickers: SPY, IVV, VOO, VTI, and QQQ). The first three track the S&P500, whereas the fourth and fifth track the CRSP US Total Market Index and the NASDAQ-100, respectively. Altogether, these 5 largest index-tracking ETFs manage over \$2.2 trillion worth of assets, accounting for roughly a quarter of the US ETFs' market values of about \$8.8 trillion. Since most large ETFs are index trackers, the rapid growth in the ETF sector reflects the growing market demand for passive investments. In 2023, the total AUM of passive equity funds first exceeded actively managed funds around the globe (Murugaboopathy, 2024). Because of the popularity of passive tracker funds, learning the nuts and bolts of equity index replications is imperative to students' career development.

Despite the proliferation of passive tracker ETFs, standard finance textbooks only explain index construction methods with verbal descriptions and simplified numerical examples (Bodie et al., 2021, 2022). Students may struggle to realize the linkage between the concept of equity indices and the practice of index replications. This article seeks to fill this void in financial education. By completing our interactive program, students will learn the principles and practical aspects of forming replicating portfolios for equity market indices. Following Girard (2024), our course design integrates the CFA Body of Knowledge, allowing students to apply concepts in the CFA curriculum with market data. For instance, this interactive guide covers security market indexes (CFA Level I) and passive equity investing (CFA Level III). We also contribute to developing creative pedagogical methods utilizing experiential learning in financial education (Dolan & Stevens, 2010; King & Jennings, 2004; Mukherji et al., 2018; Neumann, 2008; Payne & Tanner, 2011), learning-by-doing to foster students' motivation (Brunnermeier, 2017; Loviscek et al., 2003; Roden, 2013), adapting online information in finance class (Ali et al., 2009), and teaching interactively with Python (Holman & Hacherl, 2023; Jenkins, 2022; Luedtke, 2023). Moreover, past endeavors of teaching investments with computer tools (Carter et al., 2002; Kwan, 2001; Stephens, 1998; Varma & Virmani, 2022; Zhang, 2014) focus on portfolio optimizations (Markowitz, 1952). Our interactive guide contributes to teaching passive replication strategies on real-world equity indices with actual data and Python. The proposed interactive framework is suitable for both in-class demonstrations and take-home assignments. As Yahoo! Finance provides equity market data worldwide, instructors can modify the program to replicate other equity indices, leveraging students' familiarity and interest in different stock markets.

Equity Market Indices

An equity market index reflects the stock market performance. It also proxies for the market portfolio to measure investments' risk-adjusted performances and risk exposures (Jensen, 1968). Passive investors can track an index with a replicating portfolio. We solicit the Dow Jones Industrial Average (DJIA) and the Swiss Market Index (SMI) to demonstrate index replications under the commonly used price-weighted and value-weighted weighting methods among equity

indices, respectively. Instructors can replicate other indices easily with slight modifications to our code.

Constituents (component stocks) compose an equity index's investment universe. A price-weighted index indicates the average price of its constituents. In practice, we earn its returns by holding equal shares in every constituent, significantly simplifying the index replication. However, when corporate actions affect constituents' outstanding shares, the index provider must adjust its divisor. This process resolves price changes caused by changes in outstanding shares, ensuring that the price-weighted index accurately reflects the stock market performance. The US DJIA and the Japanese Nikkei 225 are well-known price-weighted indices. The DJIA, the second-oldest equity index in the US, began on May 26, 1896 (S&P Global, 2024). At its outset, with an index value of 40.94, it only tracked stocks of 12 companies. Since 1928, it has covered 30 large blue-chip stocks traded on the New York Stock Exchange and NASDAQ (Vu & Terrel, 2017). The DJIA's composition has changed over its 128-year history as new companies replaced all 12 original constituents. S&P Dow Jones Indices LLC, a division of S&P Global, currently maintains the DJIA.

A value(cap)-weighted index reflects its constituents' total market equity (capitalization) rather than their price levels. Its percentage change is identical to a value-weighted portfolio investing in constituents proportional to their relative weights in the total market equity of all constituents. Unlike the price-weighted index, a value-weighted index considers the total market equity of its constituents, providing a more comprehensive view of the market. A listed Company X with a million outstanding shares currently traded at \$20 per share has a market equity of \$20 million. Suppose the total market equity of the index is \$100 million. A replicating portfolio of the value-weighted index must invest 20% of its capital in Company X's stocks. This value-weighted method is immune to changes in constituents' outstanding shares as their market equities remain unchanged. Therefore, it is prevalent among major equity indices around the world. Prominent examples include the US S&P 500, the UK FTSE 100, the French CAC40, the German DAX, and the Swiss SMI. The SIX Swiss Exchange's SMI, launched on June 30, 1988, follows the 20 biggest stocks with high liquidity from the Swiss Performance Index (SPI), accounting for about 75% of the nation's total stock market capitalization. The SMI weights its constituents by their free-float market capitalization with a cap of 18% per stock (SIX Swiss Exchange, 2024).

In our demonstrations, we utilize full index replications that form mimicking portfolios with identical compositions to their indices. Our replicating portfolios' compositions resemble holdings of actual ETFs such as the SPDR[®] Dow Jones[®] Industrial AverageSM ETF Trust (ticker: DIA) and iShares SMI[®] ETF (CH) (ticker: CSSMI). Alternative approaches include stratification by selecting shares with similar sector exposure and proportional market capitalization to the index, sampling by choosing a small number of stocks to mimic the index performance, and synthetic replication with financial derivatives. While these alternative methods may entail lower transaction and administration costs from trading fewer stocks, they are susceptible to larger tracking errors and rebalancing costs (Dyer & Guest, 2022; Fassas, 2014; Meade & Salkin, 1989; Rudd, 1980). Moreover, from a pedagogical standpoint, full index replication aligns perfectly with the formal definition of an equity index and does not require additional statistical tools or derivatives.

Python Program for Equity Index Replications

This section describes the Python program for replicating equity indices. Code cells are executable on open-source Python distributions such as Anaconda (<https://www.anaconda.com/>) or free online Python compilers such as Google Colab (<https://colab.research.google.com/>).

Cell A: Import Packages

We import three libraries for the interactive program. The open-source **yfinance (yf)** library version 0.2.55 (<https://pypi.org/project/yfinance/>) provides access to stock market data via Yahoo! Finance's public Application Programming Interfaces (APIs) for educational and research purposes. Users should update their **yfinance** packages regularly to ensure proper functioning.

```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
def barsplot(dat, lb1, lb2):
    dat = dat.dropna()
    fig, ax = plt.subplots(1, 1, facecolor='white')
    ax.bar(dat.index, dat[lb1], alpha=0.6)
    ax.bar(dat.index, dat[lb2], alpha=0.8, width=0.3)
    rho = round(dat[lb1].corr(dat[lb2]), 4)
    plt.ylabel(f'Daily returns ($\rho={rho}$)')
    plt.legend([lb1, lb2])
    plt.show()
```

We then use **pandas (pd)** to process and transform the data. Next, we define a custom **barsplot** function with **matplotlib.pyplot (plt)** tools. It produces an overlay bar chart that compares the daily returns of the replicating strategy and its target index. The **corr** method embedded in the pandas series computes their correlation.

Cell B: Replicate DJIA

```
dji = yf.download('^DJI', period='1mo')[['Close']].pct_change()
dji.columns = ['DJIA']
url = 'https://en.wikipedia.org/wiki/Dow_Jones_Industrial_Average'
tic = list(pd.read_html(url)[2]['Symbol'])
prc = yf.download(tic, period='1mo')['Close']
dji['PWI'] = prc.sum(axis=1).pct_change()
barsplot(dji, 'DJIA', 'PWI')
```

The first line uses the **yf.download** function to download the daily market data of the DJIA (ticker: '^DJI') from Yahoo! Finance over the past 1-month interval ('1mo'). We subset the **dji DataFrame** by selecting the column of adjusted closing prices ('Close') and converting them into daily index returns (percentage changes in prices) using the **pct_change** method. Since the introduction of **yfinance** version 0.2.54, the **yf.download** function uses the default argument of **auto_adjust=True**, adjusting price-related outputs ('Open'; 'High'; 'Low'; and 'Close') for changes in the number of issued shares automatically. We rename the 'Close' column of the index returns

to 'DJIA'. Next, the `pd.read_html` function gathers tickers of constituents from the DJIA's Wikipedia page (Wikipedia, 2024a). Specifically, we extract the 'Symbol' column containing tickers from the website's third HTML table with index [2] and convert it into a `tic` list with the `list` function. Do note that the ordering of tables on the Wikipedia page may change over time. Again, the `yf.download` function downloads the adjusted closing prices for the list of tickers. The resulting `prc DataFrame` is a $T \times N$ panel data set of N constituents' daily adjusted closing prices over T days. As defined in Equation 1, the price-weighted index (pwi) on day t is the sum of adjusted closing prices of its constituents on day t scaled by a divisor (`div`).

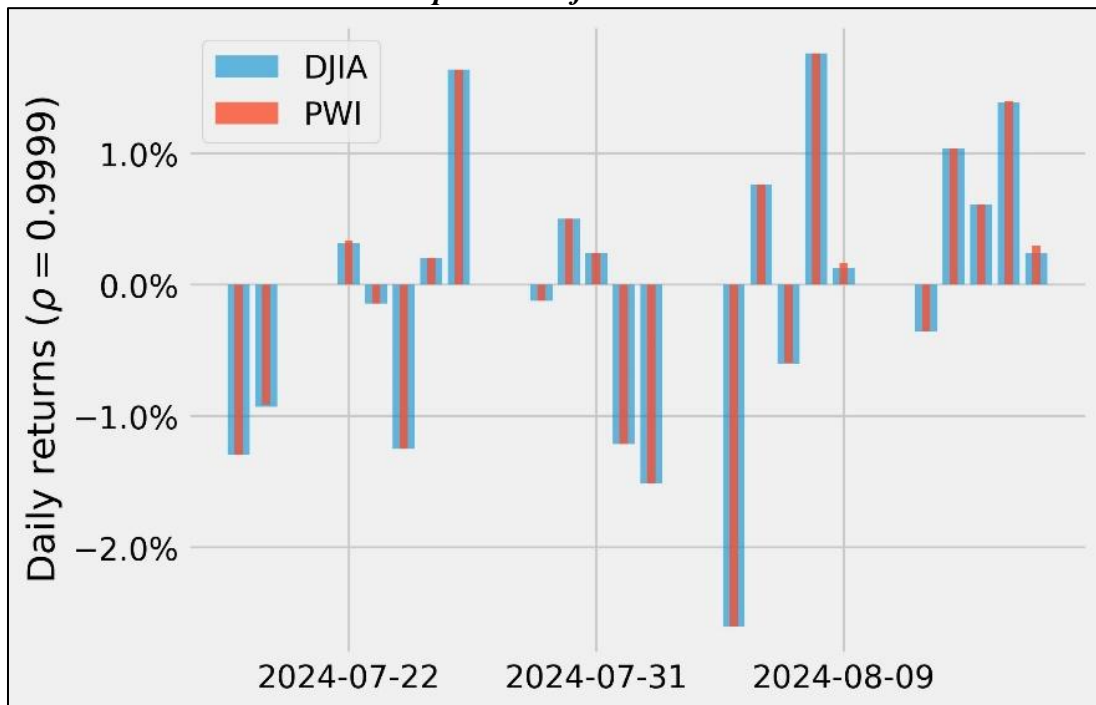
$$\mathbf{pwi}_t = \frac{1}{\mathbf{div}} \sum_i^N \mathbf{prc}_{i,t} \quad (1)$$

We use the `sum` method to compute the sum of 30 DJIA constituents' adjusted closing prices each day, identical to buying one share in each constituent. We then apply the `pct_change` method to these sums to obtain the replicating portfolio's daily returns, corresponding to the price-weighted return ($\mathbf{pwr}_{t,T}$) in Equation 2. The 'PWI' column in `dji` stores the resulting series.

$$\mathbf{pwr}_{t,T} = \frac{\mathbf{pwi}_T}{\mathbf{pwi}_t} - 1 \quad (2)$$

The custom `barsplot` function visualizes the effectiveness of our replication in Figure 2. The daily returns of the actual DJIA and the replicating PWI move in lockstep, with seemingly identical magnitudes and almost perfect positive correlation. Therefore, we successfully replicate the DJIA with a price-weighted portfolio of its constituents.

Figure 2
Replication of the DJIA



Note. The bar plot shows the daily returns of the DJIA and its PWI replication from Jul 18, 2024, to Aug 16, 2024.

Cell C: Replicate SMI

```
smi = yf.download('^SSMI',period='1mo')[['Close']].pct_change()
smi.columns = ['SMI']
url = 'https://en.wikipedia.org/wiki/Swiss_Market_Index'
tic = list(pd.read_html(url)[2]['Ticker'])
prc = yf.download(tic,period="1mo")['Close']
shr = pd.DataFrame()
for stk in tic:
    tmp = pd.DataFrame(yf.Ticker(stk).get_shares_full(),columns=[stk])
    tmp = tmp.groupby(tmp.index.tz_localize(None)).last()
    shr = shr.join(tmp,how='outer')
    shr = prc[[]].join(shr.ffill(),how='left').ffill()
    me = prc*shr
    wgt = me.divide(me.sum(axis=1),axis=0).shift(1)
smi['VWI'] = (wgt*prc.pct_change()).sum(axis=1,min_count=1)
barsplot(smi,'SMI','VWI')
```

Similar to the previous subsection, we download the adjusted closing SMI prices in the recent month from Yahoo! Finance (ticker: ^SSMI). Following that, we obtain tickers of the SMI's constituents from Wikipedia (2024b). In addition to daily adjusted closing prices, the calculations of market equities also require outstanding shares. After creating an empty **shr DataFrame**, we fill it out by downloading each constituent's outstanding shares with a for loop over **tic**. In each iteration, the **yf.Ticker** function, together with the **get_shares_full** method, acquires outstanding shares of a stock over time. The **tmp DataFrame** temporarily stores a constituent's historical share figures. Since Yahoo! Finance may update share numbers multiple times within a day, we group the data inside **tmp** by date and keep the day's last observation. The last line inside the loop forms the union between **tmp** and **shr**.

When the loop is over, we use the **ffill** (forward fill) method to replace missing values with the latest outstanding shares. Next, we match the completed **shr** to the date index of **prc** over our sampling period. The **me DataFrame** is the product of **prc** and **shr**, which stores all constituents' market equities over time. The value-weighted index (**vwi**) corresponds to the total market value of all constituents' outstanding shares. Equation 3 defines **vwi** as

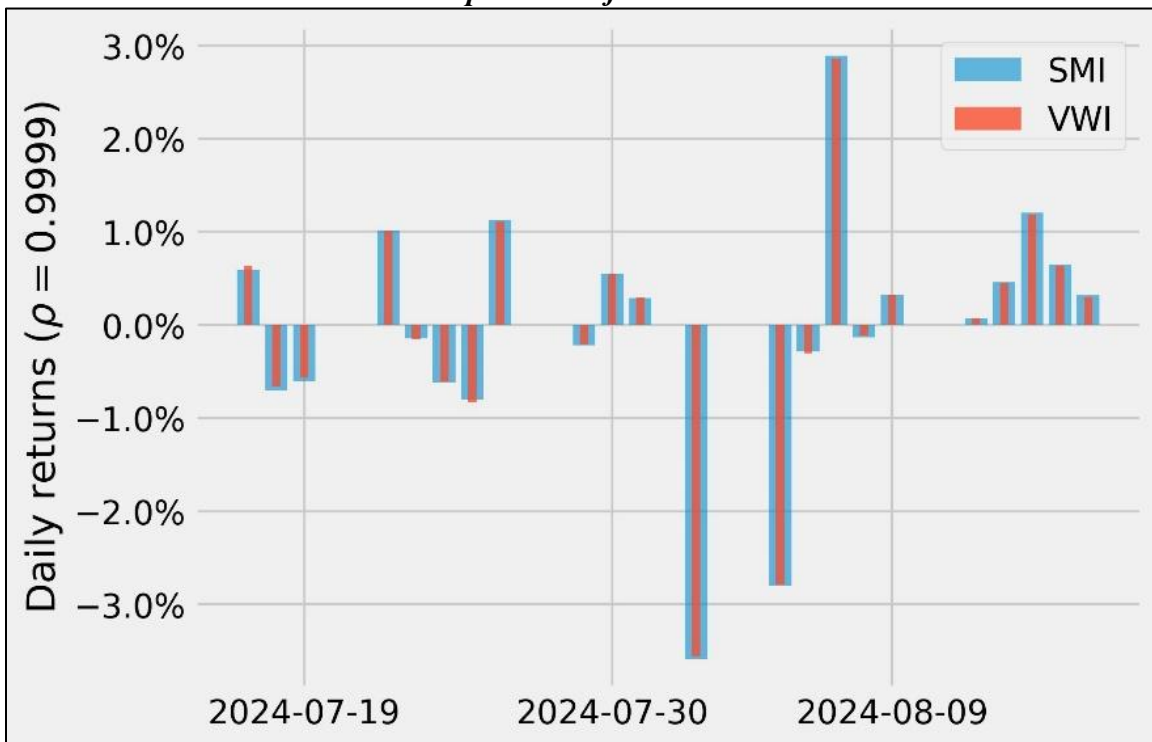
$$\mathbf{vwi}_t = \frac{1}{\mathbf{div}} \sum_i^N \mathbf{me}_{i,t}, \quad (3)$$

where the market equity of stock i on day t is the product of its stock price and outstanding shares ($\mathbf{me}_{i,t} = \mathbf{prc}_{i,t} \times \mathbf{shr}_{i,t}$). Index providers can scale their initial index levels by using different divisors. The last line computes portfolio weights for constituents according to the second line of Equation 4. Precisely, we divide every row of constituents' market equities by its daily cross-sectional sums and lag the resulting portfolio weights by one day.

$$\begin{aligned} \mathbf{vwr}_{t,T} &= \frac{\mathbf{vwi}_T}{\mathbf{vwi}_t} - \mathbf{1} = \frac{\sum_i^N \mathbf{me}_{i,T}}{\sum_i^N \mathbf{me}_{i,t}} - \mathbf{1} \\ &= \sum_i^N \left[\frac{\mathbf{me}_{i,t}}{\sum_i^N \mathbf{me}_{i,t}} \times \left(\frac{\mathbf{me}_{i,T}}{\mathbf{me}_{i,t}} - \mathbf{1} \right) \right] = \sum_i^N \mathbf{wgt}_{i,T} \times \mathbf{r}_{i,t,T} \quad (4) \end{aligned}$$

Finally, we multiply constituents' portfolio weights on day t with their realized returns from day t to day $t+1$ and sum them up cross-sectionally to generate a series of value-weighted returns ('VWI') in the **smi DataFrame**. This procedure is identical to computing the percentage change of total market equity of constituents over the same period in Equation 4. We create Figure 3 with the custom **barsplot** function to evaluate our replication. The daily returns of the SMI and its replication VWI are almost perfectly correlated ($\rho \approx 1$). The value-weighted portfolio of SMI constituents thus closely replicates the SMI.

Figure 3
Replication of the SMI



Note. The bar plot shows the daily returns of the SMI and its VWI replication from Jul 17, 2024, to Aug 16, 2024.

Cell D: Tracking Errors

```
import statsmodels.formula.api as smf
def TE(dat,lb1,lb2):
    dat = dat.dropna()
    res = smf.ols(f'{lb2}~{lb1}',data=dat).fit()
    n = len(dat)
    e = dat[lb1]-dat[lb2]
    TE1 = round(e.std()*100,3)
    TE2 = round(e.abs().sum()/n*100,3)
    TE3 = round(res.mse_resid**0.5*100,3)
return TE1,TE2,TE3
display(TE(dji, 'DJIA', 'PWI'))
display(TE(smi, 'SMI', 'VWI'))
```

We create a custom **TE** function that estimates three types of tracking errors. The **statsmodels.formula.api** library provides the **ols** function for linear regressions. Tracking errors are common in evaluating the performance of passive index trackers. Other things being equal, investors should prefer the tracker fund with the lowest tracking error. Following Fassas (2014), we consider three specifications of tracking errors (TEs) to quantify the statistical differences between an index's returns and its replication. In particular, $e_t = r_{\text{index},t} - r_{\text{replication},t}$, which is the difference between the realized daily returns of the index and its replication on day t . TE_1 is the sample standard deviation of these daily differences.

$$\text{TE}_1 = \sqrt{\frac{\sum_t^N (e_t - \bar{e})^2}{T - 1}} \quad (5)$$

TE_2 measures the sample absolute return difference, which penalizes derivations with different magnitudes equally.

$$\text{TE}_2 = \frac{1}{T} \sum_t^T |e_t| \quad (6)$$

Suppose a fund consistently beats its benchmark by $x\%$ every period. Its $\text{TE}_1 = 0$ (Roll, 1992) and $\text{TE}_2 = x\%$. The two metrics' inconsistency stems from failing to account for the fund's excess return (alpha) and risk loading (beta). To address this problem, we estimate $r_{\text{replication},t} = \hat{\alpha} + \hat{\beta}r_{\text{index},t} + \hat{\varepsilon}_t$. An ideal index tracker should have estimates for alpha and beta statistically indistinguishable from 0 and 1, respectively. TE_3 is the sample residual volatility of the regression line.

$$\text{TE}_3 = \sqrt{\frac{\sum_t^N (\hat{\varepsilon}_t - \bar{\hat{\varepsilon}})^2}{T - 2}} \quad (7)$$

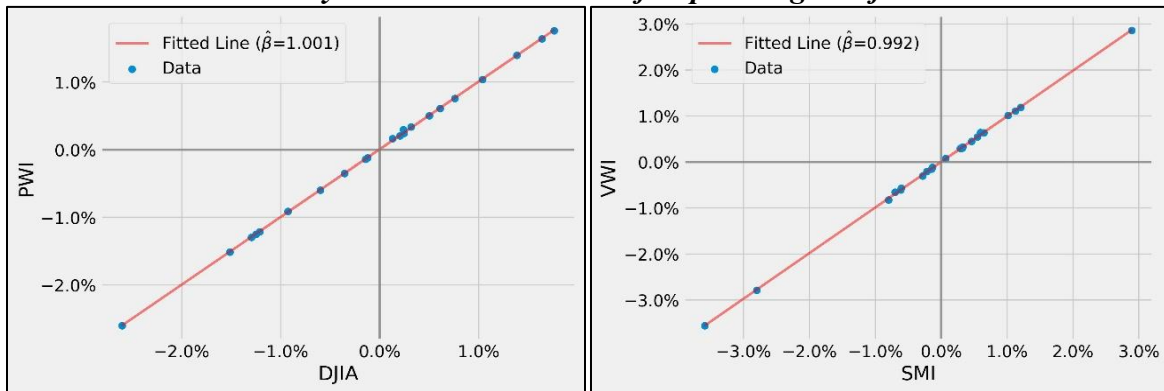
As shown in Table 1, all tracking errors are negligible. VWI achieves slightly smaller tracking errors than PWI, potentially due to the less accurate data on outstanding shares.

Table 1
Tracking Errors of Replicating Portfolios

	TE ₁	TE ₂	TE ₃
PWI vs DJIA	0.015%	0.007%	0.015%
VWI vs SMI	0.022%	0.017%	0.02%

Figure 4 shows the fitted regression lines for our index replications. Both replicating portfolios have betas close to 1 and their intercepts crossing the origin. Consistent with our previous observations, the PWI and VWI replicate their respective benchmark indices with high precision.

Figure 4
Security Characteristic Lines of Replicating Portfolios



(a) PWI vs DJIA

(b) VWI vs SMI

Exchange-traded funds

Figure 5:
Structure of ETFs

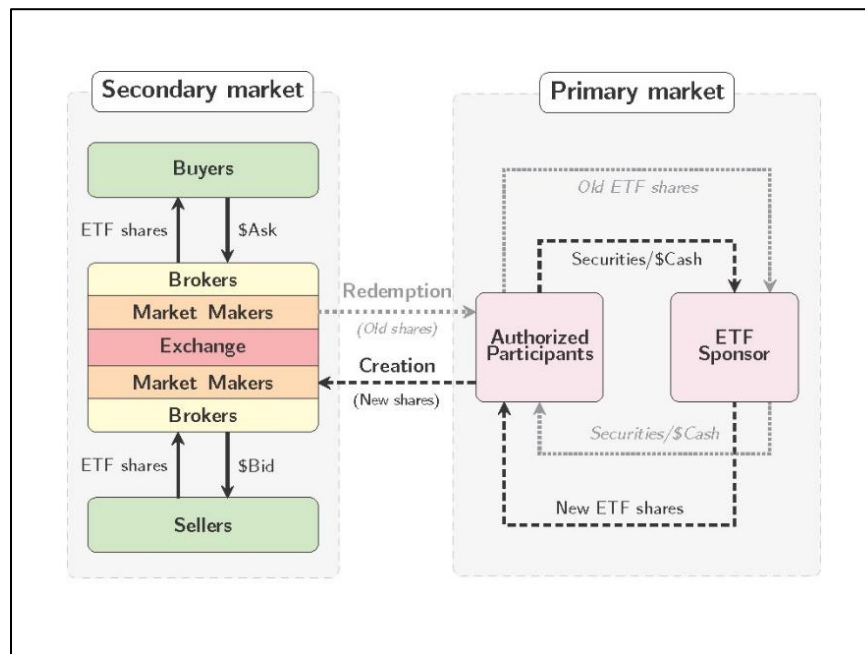


Figure 5 provides a short overview of a stylized ETF's structure. Instructors can refer their students to Thune (2024) for a detailed explanation of ETF creation and redemption. ETFs are traded on the secondary market, similar to closed-end funds (CEFs) but different from open-end mutual funds (MFs). Investors submit orders through their brokers and market makers provide liquidity to facilitate trading. The resulting transactions determine ETFs' market prices. When the price of an ETF share is above (*below*) its net asset value (NAV) per share, the fund trades at a premium (*discount*), implying that the ETF's market value is higher (*lower*) than the underlying portfolio value. Authorized participants (APs) can profit by creating or redeeming ETF shares in the primary market. Unlike CEFs, ETFs' primary market activities continue after their initial public offerings (IPOs) to correct mispricing in the secondary market.

During ETF creation, APs give underlying securities or cash to the ETF sponsor (issuer) in exchange for new ETF shares. They then sell these new shares at a premium in the secondary market. As a comparison, APs buy ETF shares at a discount from the secondary market during ETF redemption. They subsequently exchange these existing shares for underlying securities or cash from the ETF sponsor. Essentially, APs regulate the mispricing of ETFs through arbitrage. As compensation, they profit from the spread between an ETF's spot price and its NAV through these "buy low and sell high" transactions in the primary and secondary markets. Therefore, analogous to the positive relation between fund flows and fund sizes among MFs, the number of an ETF's shares increases (decreases) when trading at a premium (discount). Neumann (2009) proposes a pedagogical framework to illustrate arbitrage with DJIA and DIA ETF, which explains how APs exploit mispricing with numerical examples. Our interactive program integrates his framework by allowing users to detect real-time price discrepancies between DJIA and DIA.

Conclusion

We demonstrate replicating the price-weighted DJIA and the value-weighted SMI with market data and Python. The companion interactive program is suitable for in-class demonstrations. We can convert it into assignments by asking students to replicate other equity indices. According to Drexler et al. (2014), rule-of-thumb training effectively enhances individuals' financial literacy. The two simple rules below summarize this paper's key takeaways and reinforce principles-based training (Brau et al., 2015; Skimmyhorn et al., 2016).

Rule 1 To track a price-weighted index, invest the same number of shares in each constituent.

Rule 2 To track a value-weighted index, invest in each constituent according to the weight of its market capitalization over the total market capitalization of all constituents.

Our replications are subject to caveats. First, we only consider price returns (capital gains/losses) akin to typical equity indices (Lin et al., 2022). Investors do receive dividend payments from stocks in the replicating portfolio. Second, equity index providers commonly use free-floats (publicly traded and unrestricted shares) instead of total issued shares when computing market equities. Therefore, a low tracking error hinges on good-quality data and information systems (Broby, 2011). In practice, index providers and trackers obtain the latest prices and free-floats of index constituents from stock exchanges. Third, we ignore transaction costs and taxes. On paper, we can replicate the DJIA by buying one share in each constituent. However, odd-lot transactions are typically costly (Davis et al., 2017). Investors with insufficient capital to replicate equity indices through round-lot transactions should instead consider tracker ETFs to improve their after-cost investment performance.

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Experimenting and Testing the Construction of Behavioral Portfolios in a Classroom

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This paper offers insights into experiential learning on the basis of the belief that today's finance students are future financial analysts. The paper examines various behavioral aspects that are normally included in an undergraduate course syllabus of portfolio management. The main objective is to narrow the gap between research findings in behavioral portfolios and popular topics in the undergraduate course syllabus.

The ultimate objective of this paper is to benefit from experiential learning to prepare finance students to address the realities of financial and nonfinancial markets. The results of the relevant nonparametric tests can be outlined as follows. (a) The distinction between risk averse and taking is well comprehended by the students, (b) the positive relationship between risk and return may reverse in contrast with the MPT assumption, (c) the students comprehend the differences between different financial and nonfinancial markets distinctively, (d) investors in financial and nonfinancial markets may deviate from conventional risk averse and risk taking to choose investments on the basis of availability heuristic (e.g., popularity), (e) the latter may result in mixed results, which illustrates the origin of market anomalies, (f) investment with an availability heuristic attitude is a resort during unexpected events (COVID-19 in this paper), (g) male students tend to risk taking, whereas the opposite is true for female students, (h) home country bias is further illustrated and emphasized, and (i) all the results resemble the outcomes of related previous studies, which fulfills the ILOs of undergraduate portfolio management courses in addition to preparing students facing the realities of investment in financial and nonfinancial markets.

Keywords: Experimental behavioral portfolio, Affective attitudes, Return anomalies, Prospect theory, Availability heuristic

JEL: G12; G15; C82

Introduction

The practice of portfolios as investment funds has benefited from the mathematical assumption of efficient and minimum variance mathematical algorithms that have also extended the economic assumption of rationality. Nevertheless, this field is never free from semantics. The players in the world of investment include those who are literate or illiterate about the mathematical algorithms that control their behavior. This explains the movements from rational to irrational investment behavior. When practitioners deviate from the rational assumption of efficient portfolios, their behavior is referred to as irrational but is actually associated with the anomaly of returns. Therefore, irrationality is a reality that is worth examination at all times. The outcomes of many studies in behavioral finance offered significant evidence about the anomaly of investment outcomes. Anomalies are outcomes of differences in attitudes and emotions. In this sense, this issue is quite costly and has also been examined in the vast literature concerning the effects of transaction costs. In addition, the timing of an investment decision may not allow practitioners to examine investors' rationality in advance. This is the main reason for the popularity of issues related to behavioral finance that involve experimentation.

In this work, students in portfolio theory (FINC 415/4204) classes at American University in Cairo were considered potential investors throughout two subsequent semesters, Fall 2021 and Spring 2022. This empirical view reflects the reality that today's students are tomorrow's economic agents (Sjöberg & Engelberg, 2009). This view is helpful in many ways, as follows.

First, experiential learning offers students chances for personal development, which is a significant determinant of success later in their career (Kohn, 2024). Second, as behavioral finance is, on the one hand, concerned with investors' differential attitudes and beliefs, experiential learning offers students (being tomorrow's traders and/or investors) chances to examine the outcomes of their choices without incurring costs or facing pitfalls of risk (Batty et al., 2020; Langran, et al., 2009; Mancone et al., 2024; Saunders, 2001). Third, experiential learning has a significant and positive effect on modeling equity market investment performance, such as liquidity (Aharon et al., 2023; Payne & Tanner, 2011). Fourth, experiential learning helps deepen our understanding of the extent to which financial knowledge is connected to rational or irrational investment decisions.

Experiential learning is much more challenging than merely delivering a topic in a lecture. Experiential learning involves many elements, namely, (a) designing the differentiation in the scope and level of knowledge offered to undergraduate and postgraduate students, (b) reading extensively the research results of previous related studies to design elements of an experiment that reflects what happens in reality, and (c) performing rigorous statistical tests to verify the significance of the outcomes. Usually, a conventional lecture addresses in-class routine assignment, where the only concern is to perform it and submit it within class time. As the objective of an experiment should not be revealed in advance to rule out bias, the critical question is how a lecturer ensures students' seriousness. The authors discussed and agreed on two procedures to be carried out at the beginning of each class. First, real-life stories that take up to 3–5 min as an introduction to the topic are used. The objective is to focus the students' attention on what they are about to deal with. Second, very recent data are used to draw the attention of the students that the underlying topic is to examine what is actually happening in real life.

As lectures are delivered in computer labs connected to the internet, a number of issues have been examined, such as the risk–return tradeoff, efficient portfolios, diversification across different

markets, investment in risk-free securities, and investment in times of uncertainty. These issues have been examined empirically via real-life data.

Motivation

Two motivations drive the authors to experiment with the construction of behavioral portfolios in a classroom. The first motivation is common, which is to fulfill the ILOs in an undergraduate portfolio management course. The second motivation is to expose finance students to the realities of investment in financial and nonfinancial markets before they graduate. The latter reflects the intrinsic value of experiential learning.

Experimental Contribution

This paper contributes to and updates the understanding of the extent to which attitudes and individual behavioral differences may affect the construction of portfolios.

Experiential objectives

This paper aims to fulfill the following objectives.

1. Examine the significance of the behavioral differences in the risk–return tradeoff.
2. Examine the significance of the behavioral differences in investing in diversified markets.
3. Examine the significance of the behavioral differences when investment outcomes are uncertain.
4. Examine the significance of subjective choices to invest in risk-free instruments.
5. Examine the gender effects on investment in financial and non-financial markets.
6. Examine the effect of home country bias on investments in financial and nonfinancial markets, especially because the place where experiments are conducted is an international university that includes many nationalities.

The rest of the paper is organized as follows. The first section discusses the effects of psychological attributes when the risk–return tradeoff is considered. The second section discusses the behavioral aspects of portfolio construction. The third section discusses experiments on the risk–return tradeoff. The fourth section discusses the experimentation of the diversified n-asset portfolio. The fifth section discusses the experimentation of discretionary choices of n-asset portfolios. The sixth section discusses the experimentation of prospect theory with uncertain outcomes. The seventh section discusses the experimentation of investment in risk-free government securities. The eighth section discusses the effect of gender on the construction of diversified portfolios. The ninth section concludes.

How do Students Grasp the Behavioral Foundations of Portfolio Construction?

Usually, students are introduced to normative portfolio theory, which is well known as “Modern Portfolio Theory” (*hereinafter*, MPT), where a typical target is to reach an “Efficient Portfolio” (Markowitz, 1952). The latter assumes that the investor is willing to reach a target return at a prespecified degree of variation (e.g., risk) or to reach a target degree of risk associated with a prespecified rate of return. Students can soon realize that the MPT is merely a mechanical construction that normally takes approximately one hour of mathematical and statistical

computations. Nevertheless, as students are treated as economic agents, behavioral differences must be introduced to them to experiment with the outcomes of MPT and the “behavioral portfolio” (BP). At this stage, a discussion of “affective attitudes” is a normative foundation of BP that can be outlined as follows.

Affective Attitudes and Risk-Return Tradeoff

The risk–return tradeoff has been examined under different assumptions. The early beginning was the assumption made by Sharpe (1964) in the capital asset pricing model, which assumes a positive relationship between volatility and excess returns. However, this relationship was negative in other studies, such as those of Kaustia et al. (2009), Nelson (1991), Shefrin (2001), and Weber et al. (2013). A turning point in this relation has been introduced by considering the psychological attributes of the risk–return tradeoff. Kempf et al. (2012) argued that affective factors such as emotions, attitudes, and feelings toward a specific asset can best describe the bias in investors’ expectations about risk–return trade-offs. That is, affective attitudes are most likely to be engaged in a financial context where market participants are expected to assess the risk and return prospects of securities. Moreover, investors may end up constructing an underdiversified portfolio, mainly owing to their affective attitudes toward certain stocks, which are believed to produce higher returns at lower risks than the average investment. Glore and Gasper (2000), Lucey and Dowling (2005), Virlics (2013), Etzioni (1988), Hanoch (2002), and Barber and Odean (2001) argue that the term “affect” can be broken down into emotions, which can be defined as “affective states”, and attitudes, also characterized by “affective dispositions” (Chui, 2001).

Slovic et al. (2002) and Livet (2010) argue that affect heuristic explains how people in general develop expectations and make judgments about the risk of a particular security from a global affective perspective. Therefore, regardless of the fact that undisciplined decisions may lead to short-term gains, investors may overlook the risks inherent in stocks. This argument explains why a bull market will experience upward movement, causing the market risk premium to fall (Peterson, 2007).

Lucey and Dowling (2005) argue that when investors deviate from rationality and optimal decision-making behavior, “a satisficing behavior” or, at large, satisfactory alternatives seem very efficient (Simon, 1987; Lo & Repin, 2001). However, Kaufman (1999) offered the opposite view that extreme emotional states may not help investors make efficient judgments.

Experimenting with the Psychology of Portfolio Diversification

Behavioral finance is an area of study that focuses on assessing the psychological factors that influence the behavior of investors in financial markets (Kahneman & Tversky, 1979; Kapoor & Prosad, 2017; Shefrin, 2002). Unlike the classical school of finance, which assumes that investors are rational and make decisions on the basis of all available information, behavioral finance acknowledges that people are not always rational and may be influenced by cognitive and emotional biases. Behavioral finance has been increasingly gaining popularity in recent years, especially since the 2008 financial crisis, which was in part attributed to the irrational behavior of investors (Kahneman & Tversky, 2013). While efficient market hypothesis (EMH) theory assumes that financial markets are always efficient and that prices reflect all available information, behavioral finance acknowledges that investors may not always behave rationally and that prices may not always reflect all available information (Smith, 2017).

Portfolio management also involves managing securities in accordance with an investor's desired returns and risk levels, with the aim of diversifying investments to reduce overall risk. Nevertheless, behavioral finance involves examining investors' psychology and integrating the behavioral characteristics of investors into asset pricing models (Benzion & Yagil 2003). In addition to financial factors, behavioral finance accounts for other factors that impact an investor's decision-making, such as how basic information is interpreted. Barberis and Thaler (2003) assert that behavioral finance helps explain how investor behavior and investment decisions are shaped.

How do Students Realize the Risk-Return Tradeoff?

The widespread relationship between risk and return is a significant guide to many investment decisions in the market. Investor decisions and behavior are influenced by emotional factors that exist within the financial market. These emotional factors differ from cognitive factors, which are concerned with how individuals use and organize information. Emotional factors, on the other hand, relate to the affective dimension of an individual's information record (Shefrin & Statman, 2000). Investment decisions can be affected by various emotions, such as ambition, fear, hope, pride, and regret. Common emotional factors that impact financial markets include cognitive dissonance, regret avoidance, hedonic correction, the predisposition effect, the lure of easy money, risk aversion, and the break-even effect.

Pedagogy: General experimental settings

In a general experimental setting, the students did not know in advance the details about the topic being discussed in the lecture. Nevertheless, a generic understanding of the topics of the lectures is necessary to (a) measure the students' understanding of the respective concepts without causing cognitive biases and (b) determine the students' quantitative differences between MP and BP. In this case, the students were asked to read beforehand about certain related concepts holistically, such as Investopedia as a general source of reading or other sources they are familiar with, which serves as an attempt to induce self-learning.

In the next three experiments, the same experimental settings were used as follows. On the day of class, the students were handed over a password-protected Excel data file (accessed simultaneously via the Black Board). When students were allowed to open the file, every student was asked to rename the file as his/her name and University ID. The students were asked to construct MVPs via the Markowitz algorithm. All the experiments are repeated in two back-to-back lectures delivered in the same computer lab and on the same day.

Experiment 1: How do Students Observe a Risk-Return Tradeoff?

- The objective of this experiment is to validate the risk–return tradeoff as a foundation of the minimum variance portfolio (MVP).
- Students were offered two minutes to think about choosing one risk attitude, either risk averse or risk taking, before they opened the Excel data file. This procedure rules out any source of bias. Students' satisfaction and engagement are addressed through offering the students a chance to move from one risk attitude to the other. The detailed statistical results are reported in Table (1).

Table 1
Significance of Aptitudes in Risk Taking and Risk Averse

Mann–Whitney Test	Single Market			
	Portfolio Variance		Portfolio Return	
	Averse	Taking	Averse	Taking
N	23	17	23	17
Mean	0.0116%	0.0281%	-0.0161%	-0.1689%
Mean Rank	12	32	29	9
Z stat (2 tail)	-6.245***			
Bernoulli Indicator Function of Sample Selection Bias	9.09495E-13			
Prob. Risk Averse (Taking)	57.500% (42.500%)			
Max Likelihood of Risk Averse (Taking)	12.68% (2.07%)			

*** Significant at the 1% level

The results in Table (1) show that the two risk attitudes differ significantly in terms of portfolio variance and returns. Notably, testing the statistical significance of the differences between risk attitudes extends the scientific criteria for measuring risk attitudes (Colasante & Riccetti, 2021; Metzger & Fehr, 2018). The common statistical significance in the risk–return relationship offers an indication of the absence of biases due to students' seating. In the case of the riskiness of the portfolio, risk-taking is associated with a greater degree of variation than is risk aversion. Indeed, this result offers statistical, but partial, support for the use of variance as a measure of risk. Nevertheless, the positive association between risk and return is reversed in contrast with the MPT assumption. That is, in the case of risk taking, as risk increases, the weighted average return decreases.

Learning Outcomes

Therefore, the positive relationship between risk and return is merely a behavioral assumption that may not be realized in reality. The reverse risk–return relationship offers further support for overconfidence and biased self-attribution (Daniel et al. 1998). At the end of each experiment, the instructor opened a freelancing discussion with the students about what approach (Modern Portfolio Theory or Behavioral Portfolio) they would exercise in real life should a student take on a role as a fund manager.

Testing for Sample Selection Bias

The robustness of the results requires an examination of sample selection bias, as the numbers of risk-averse and risk-taking students (N) differ. Although Heckman's (1979) methodology for testing sample selection bias has been popularized in the case of survey data, the nonrobustness of this methodology has been addressed via maximum likelihood using probit estimation (Bastos et al., 2022). Nevertheless, probit estimation does not fit the data in these experiments for two reasons. First, these experiments do not include covariates. That is, other exogenous variables affect the construction of behavioral portfolios. Second, the response variables (portfolio weighted average returns, variances) include constant (e.g., common) values that deter the estimation process. In this case, as the variable under consideration is dichotomous (for example, 1 for risk

averse, 2 for risk taking, etc.), the Bernoulli distribution is relevant for the estimation of the probability of sample selection bias, which is computed as follows (Ross, 2020).

$$p(\text{sample}|\theta) = (\theta)^{n_1} (1 - \theta)^{n_2} \quad (1)$$

where $p(\text{sample}|\theta)$ = Bernoulli indicator function of sample selection bias; θ = probability of being risk averse; n_1 = number of risk-averse students; $1 - \theta$ = probability of risk-taking; and n_2 = number of risk-taking students.

The maximum likelihood (ML) of the probability of being risk averse is estimated via the binomial algorithm as follows.

$$ML = {}^n C_k \theta^k (1 - \theta)^{n-k} \quad (2)$$

where ${}^n C_k$ = Combinations of possible k risk-averse students that can be formed from n students, and by definition, $(1 - \theta)$ is the probability of risk taking. ML serves as an indicator of the maximum probability of occurrence. The ML of θ is estimated via iterations of the optimization algorithm, which is integrated into MS Excel as Solver. The optimization structure is as follows: (a) the objective function is to maximize the ML ; (b) by changing the probability of occurrence θ , the constraint is $0 < \theta < 1$.

With respect to aptitudes, the results in Table (1) show that most students favor risk-averse attitudes, as higher ML is associated with a greater probability of being risk averse. Notably, the likelihood of sample selection bias is quite small, as the value of the Bernoulli indicator function is quite small.

Experiment 2: How do students learn the pros and cons of diversification across different markets?

As portfolio diversification requires a specific understanding of different financial markets, the empiricism of portfolio construction requires an examination of the risk–return tradeoff across different markets.

- The students were handed over an Excel data file that included data about three different markets: foreign currencies (G20 currencies), metals, and common stocks.
- The issue of experimental validity is examined by running the same experiment in the subsequent class. Students do not have time to exchange information with each other; therefore, bias is ruled out. The detailed statistical results are reported in Appendix (a).

The results in Table (2) show that the construction of portfolios in different markets offers further perspectives that reflect the empiricism of the required rate of return. These results can be outlined as follows. First, the distinction between risk averse and risk taking is still statistically significant, as the average variance of each portfolio being constructed assuming risk averse is less than risk taking. Second, in terms of portfolio average returns, mixed results are reported in different markets. That is, risk-averse students' average portfolio returns in foreign currency and metal markets are greater than those of risk-taking students, with the exception of one common stock market. Notably, the ML shows that risk aversion is favored. In addition, the value of the Bernoulli indicator function is quite small, which rules out sample selection bias. Third, students

understand and treat the asset market differently, which reflects the fact that the asset market is distinct; therefore, there is not a universally required rate of return.

Learning Outcomes

Financial and nonfinancial markets require different investment attitudes.

How do Students Assess the Risk-Return Tradeoff of the n-Assets portfolio?

The experiments were extended to the construction of five-asset portfolios. The objective is twofold. First, we offer the students real-life chances of further verifying the positive risk–return relation inherent in the two-asset MPT classic examples. Second, we examine the effects of *n*-assets on the risk–return tradeoff, considering that a well-diversified portfolio is not defined by a specific number of stocks (Statman, 1987; Oyenubi, 2019; Zaimovic, et al., 2021). The results are reported in Table (2).

Table 2
Significance of the risk–return tradeoff across different markets: Five-asset portfolio

Mann–Whitney Test	Portfolio Variance		Portfolio Return		Z stat, 2 tails
	Averse	Taking	Averse	Taking	
N	53	55	53	55	
Mean Rank	27	81	82	28	
Mean for Foreign Currency Portfolio	0.000187%	0.001744%	-0.01464%	-0.02448%	-10.344***
Mean for Metals Portfolio	0.007795%	0.010395%	0.031929%	0.006214%	-9.745***
Mean for Common Stock Portfolio	0.01866%	0.031901%	0.08752%	0.040538%	-10.344***
Bernoulli Indicator Function of Sample Selection Bias	3.08149E-33				
Prob. Risk Averse (Taking)	49.074% (50.926%)				
Max Likelihood of Risk Averse (Taking)	7.6612% (7.1142%)				

*** Significant at the 1% level

The results in Table (3) offer extended evidence of the distinction of variance in the cases of risk aversion and risk taking. That is, the former is less common than the latter across different asset markets, which matches the assumptions of MVP (Markowitz, 1952). Extended evidence on the behavior of portfolio average returns also shows that risk aversion is associated with greater returns than risk taking is (Chhatwani, 2024; Levy, 2022; Kimball, 1993; Dow et al., 1992). These results offer tactics that experiential educators can further discuss with confidence in a class lecture. An interesting outcome is that the inverse relationship between risk and return does not depend on either the number of assets in the portfolio or risk attitudes.

Learning Outcomes

Risk aversion (taking) remains merely a behavioral attitude that does not fulfill a certain objective—a conclusion that has been in market for many years (Vlaev et al., 2009; Hoffmann et al., 2015; Weber & Milliman, 1997). That is, investors may assume a risky position in a market hoping to end up with higher returns, but the reality of the market offers the opposite (Braido et al., 2011; Lee et al., 2015; Xia et al., 2014).

Notably, sample selection bias is still quite small. In addition, ML offers indications that in the case of considering different markets, investors tend slightly to adopt a risk-taking attitude without thorough calculations of the expected outcomes in advance (Conlin e al., 2015). Indeed, these results extend significant conclusions from related studies discussing the significant role of stock analysts' recommendations (Von Gaudecker, 2015; Guiso & Jappelli. 2005; Abreu & Mendes, 2010; Bianchi, 2018; Chauhan & Dey, 2020; Cole & Shastry, 2009). These results are supported by field research and offer extended experiential learning lessons to finance students being regarded as future investment advisors.

Testing for Robustness: Consistency of Students' Understanding of Risk Averse (or taking)

Given that the students were offered a free hand choosing five assets from a pool of different financial and nonfinancial assets and that the same settings were applied to a different class with different groups of students, it is worth examining the robustness of the results. The results are reported in Table (3).

Table 3
Tobustness of the Risk-Return Affective Attitudes: Students' Understanding of Risk Averse (or taking)

Mann–Whitney Test	Portfolio of Foreign Currency, Metals and Common Stocks			
	Risk Averse		Risk Taking	
	Portfolio Variance	Portfolio Return	Portfolio Variance	Portfolio Returns
N (Class 1) (Class 2)	(28) (25)		(31) (24)	
Mean Rank (Class 1) (Class 2)	(27) (27)		Foreign Currency (28) (28)	
			Metals (17) (42.21)	
			Common Stocks (28) (28)	
Z stat, 2 tail (Class 1) (Class 2)	0.000		0.000	
Bernoulli Indicator Function of Sample Selection Bias	1.11022E-16		2.77556E-17	
Prob. Risk (Return) Affective Attitudes	52.830% (47.170%)		56.364% (43.636%)	
Max Likelihood of Risk (Return) Affective Attitudes	10.9255% (7.7766%)		10.7966% (1.7998%)	

The results in Table (3) show that differences between risk averse and risk taking across different groups of students are statistically significant.

Learning Outcomes

This result must be considered an indication of the extent to which students' awareness of risk attitudes is clear enough. This clarity is a satisfactory sign of effective learning. Therefore, the behavioral aspects of risk taking and aversion are clear and distinctive, which, in turn, are significant indicators of the robustness of the results.

Experimenting students' understanding of the limits of portfolio diversification

Investors' behavior in financial markets can be heavily influenced by herd behavior, where investors imitate the decisions of others. This behavior can lead to distortions in market efficiency and volatility. Mental accounting is also an important concept in behavioral finance, where individuals evaluate the results of their choices briefly and record them in separate mental accounts, which may lead to irrational investment decisions (Thaler, 1999). Mental accounting often causes investors to evaluate investments separately, leading to poor investment preferences and timing.

According to traditional models, investors' subjective probabilistic beliefs are assumed to be objectively accurate, thereby implying market efficiency. In such a scenario, the primary aim of a portfolio is to manage an investor's consumption flow's risk profile, which is determined by their initial assets (Hoffmann, et al., 2010). In the field of portfolio research, empirical studies reveal a range of anomalies and issues. Modern portfolio theory seeks to explain the functioning of capital markets through transactions; it does not provide recommendations on how to construct investment portfolios. That is, modern portfolio theory operates on the basis of certain principles, some of which investors are familiar with while others remain unknown. One of its underlying assumptions is that investors are always rational and strive to increase their wealth, which is ultimately untrue. Given these limitations, financial advisors often face communication barriers when attempting to discuss portfolios with clients via the framework of modern portfolio theory (Curtis, 2004). Owing to the limitations of MPT, behavioral portfolio theory (BPT) has emerged as a descriptive alternative to Markowitz's mean-variance portfolio theory, as it combines the creation of portfolios and security design (Shefrin & Statman, 2000). BPT builds on Roy's (1952) safety-first approach. Kahneman and Tversky (1979), Tversky and Kahneman (1992), and Thaler (1999) suggest that individuals use the mental accounting approach to divide their current and future assets into separate and nontransferable parts, making distinct mental calculations that are treated differently. BPT encourages investors to view their portfolios as a collection of sub portfolios, each suitable for specific mental accounting. Das et al. (2011) combined the essential features of modern portfolio theory and BPT to create a new mental accounting (MA) framework. Many investors apply primitive investing strategies that, for instance, do not consider existing correlations between targeted assets (Gubaydullina & Spiwoks, 2009; Rodríguez et al., 2021).

Experiment 3: Discretionary choices and students' limits in understanding portfolio diversification

The empiricism of the abovementioned arguments was carried out as follows.

- Students were asked to use <https://www.investing.com/> to look at the profile of the different markets that help them formulate certain attitudes and expectations (Fehle et al., 2005).

The students then downloaded returns for three different markets: ten common stocks listed in an index, ten commodities, and ten currencies.

- Every student was asked to construct a five-asset portfolio assuming one of three attitudes: risk averse, risk taking and availability heuristic. The latter reflects subjective choices that are usually examined in the relevant literature as indicators of irrational choices. The detailed statistical results are reported in Appendix (b).

In this experiment, the students were offered wider free choices, namely, either to adopt risk aversion or risk taking or ignore both and invest in an asset (financial or nonfinancial) on the basis of its popularity (definitely bound by the knowledge of the students), which reflects availability heuristic. Notably, experiential learning in this experiment requires more time and, in advance, general readings about the markets under consideration. The specific reading recommended by experiential educators is necessary.

The results in Appendix (b) show interesting further behavioral aspects of portfolio construction. First, less risk is associated with risk averse than with risk taking, but availability heuristic is associated with a mixed degree of variation, which extends the findings of related studies (Dhami, 2016; Lichtenstein et al., 1978; Powdthavee & Riyanto, 2015; Piotrowski & Bünnings, 2024; Shah & Butt, 2024; Tversky & Kahneman, 1974; Wagenaar, 1991). Second, risk matters more than return with respect to comparisons between different financial and nonfinancial markets. Third, in the cases of commodities and foreign exchange, a positive relationship between risk and return is observed. Indeed, this result shows that wider comparisons between different financial and nonfinancial markets exemplify market anomalies, which offers an excellent chance for experiential educators to offer students an empirical chance to observe market anomalies. Fourth, the students still favor risk-averse attitudes, as ML is greater in cases of risk-averse probability.

Learning Outcomes

This is further evidence of what is cited in the literature as a positive association between subjective choices and return anomalies (Pfiffelmann, et al. 2016; Statman, 2008).

Experimenting prospect theory with uncertain outcomes

Kahneman and Tversky's (1979) prospect theory incorporates psychological factors into economic models and predictions. Unlike expected utility theory, prospect theory is based on experimental research and is mathematically formulated. The theory suggests that individuals can make irrational choices and that psychological factors can cause individuals to deviate systematically from rationality. Common errors made by investors in the same direction can also cause investor sentiment (Shu & Chang, 2015). In this sense, the shifts in investors' investment attitudes during the COVID-19 pandemic must be examined.

Experiment 4: How did students perceive the effects of COVID-19?

- Students were asked to use <https://www.investing.com/> to download monthly returns on commodities listed in the Dow Jones Commodity Index for two years before the outbreak of COVID-19 and monthly data for one year after the outbreak of COVID-19.

- Students were asked to construct a four-commodity portfolio assuming one risk aptitude only: risk averse, risk taking, or availability heuristic. The objective is to examine the extent to which investors' choices during the pandemic were rational. The detailed statistical results are reported in Appendix (c).

The objective of this experiment is to compare investors' risk attitudes during an unexpected event; the most recent is COVID-19. As that event is worldwide, the convenient measure is the explanatory power of systematic risk \bar{R}^2 . The results in Appendix (c) show that before COVID-19 broke out, risk takers were exposed to greater systematic risk (44.93% associated with a negative weighted average daily return of -1.68%) than were risk averse and availability heuristic risk takers. After the pandemic broke out, confusion exposed investors to resort to availability heuristic but actually exposed themselves to greater systematic risk (82.32% associated with higher weighted average daily returns of 0.2613%). Nevertheless, the ML shows that risk taking is associated with the highest ML. It is obvious that during widespread risk, investors still believe that higher risks may lead to higher returns, which is not observable. This result is considered extended evidence on the effect of affective aptitudes that drive investors' investment decisions during an unexpected event.

Learning Outcomes

In terms of prospect theory, the results show that deviation from rationality results in higher returns. These results reflect the empiricism of "irrational excellence" (Shiller, 2000).

Experimenting with the Students' Understanding of Risk-Free Rates of Return

Experiment 5: How do Students Understand the differences between Investments in Risk-Free Securities, Risky Investments and the Country Effect?

As the term "Risk" causes confusion in the field of finance at large and investment in particular, students being treated as economic agents need to materialize the difference between risk as a degree of variation and risk as a loss of value. In addition, a troubling topic in both monetary economics and financial investment is the concept and practice of the "risk-free rate of return," simply because it is not literally free of all risks and is confused with fixed income returns. Therefore, there is a constant need for students to be aware of those concepts, which is the main objective of this experiment.

This experiment examines the returns on portfolios of risk-free securities (government bonds) issued by different countries. The goal is to examine the country's effect (e.g., a favorable country by investors). The students were asked to use <https://www.investing.com/> to choose the country in which they wanted to invest. The students downloaded the yields of all securities issued by a respective country's government. The detailed statistical results are reported in Appendix (d). The results show that the differences in students' preferences across countries in which they like to invest are statistically significant.

Learning Outcomes

The highest percentage of preference to invest in the home country (Egypt) offers extended evidence on the results of previous studies about home country bias (Abreu et al., 2011; Ke, 2010;

Eliasa, 2022; Pitterle, 2022). Nevertheless, there is a need to further examine country selection bias since students' seating may affect their choices. Usually, students in one class sit relatively close to each other, so they may have had some exchange of information.

Risk-Return Tradeoff and Portfolio Diversification: The Gender Effect

This part shows the results of portfolio construction being carried out by male and female students, taking into consideration that no experiment was separated between them. All the students sat in the same computer lab. The gender effect has been examined in several studies. For example, see Barke (1997), Slovic (1996) and Finucane et al. (2000). The detailed statistical results are reported in appendix (e).

The results in Appendix (e) compare the risk attitudes of male and female students when constructing a diversified portfolio. The results show that the highest ML (18.525%) is associated with male students adopting a risk-taking attitude, whereas female students are associated with the highest ML (19.674%) being risk averse. Notably, sample selection bias is ruled out, as the value of the Bernoulli indicator function is quite small in every risk attitude. Notably, the gender effect on diversification is mixed, as male (female) students prefer different markets.

Learning Outcomes

That is, participants share a homogeneous understanding and perception of every single risk attitude (Cheng, 2019; Maxfield et al., 2010). The mixed results of gender effects extend the conclusions reached by Nelson (2015), Marinelli et al. (2017), and Vlaev et al. (2008). Nevertheless, the results in appendix (e) show that a significant gender effect is observed in the risk-averse and risk-availability heuristic commodity portfolios. That is, in the case of risk-averse individuals, the mean ranks for females are greater than those for males, a finding that extends other related studies (Almenberg & Dreber, 2015; Beyer & Bowden, 1997; Charnessa & Gneezy, 2012; Cohn et al., 1975; Deaux & Ennsuiller, 1994; Dake, 1991; Jianakoplos & Bernasek, 1998; Harris & Jenkins, 2006; Olsen and Cox, 2001; Victor & Riley, 1992). The authors may argue that commodities are much closer to people's everyday lives than other types of investments are. Therefore, males may have commodity preferences over females in this respective experiment, which extends the conclusions of (Loibl & Hira, 2011).

Table 4
Portfolio Diversification across Different Markets: The Gender Effect

Financial Markets	Test Statistics (Mann–Whitney)	Male (Female)	Bernoulli Indicator Function of Sample Selection Bias [Prob. Risk (Male) (Female)] {Max Likelihood of Risk (Male) (Female)}
Financial Stocks	Z Stat [Asymptotic Sig. (2-tailed)] N (Males = 25) (Females = 33)	-0.4946 (0.6208)	3.46945E-18 [(43.103%) (56.897%)] {(10.531%) (1.1425%)}
	Mean Rank: Males (Females)	30.76 (28.545)	
Commodities	Z Stat [Asymptotic Sig. 2-tailed] N (Males = 25) (Females = 33)	-0.149 (0.881)	
	Mean Rank: Males (Females)	29.88 (29.21)	
Foreign Currencies	Z Stat [Asymptotic Sig. 2-tailed] N (Males = 25) (Females = 33)	-0.478 (0.631)	
	Mean Rank: Males (Females)	28.28 (30.424)	

Table (4) reports the results of the gender effect apart from risk attitudes. The results show that males prefer diversification across different markets, as the ML (10.531%) for males is greater than that for females (1.1425%).

Conclusion

An experiential concern that experiential educators must consider is to discuss the final results with the students being tomorrow’s financial analysts. This discussion not only offers feedback to the students but also, most importantly, offers influential evidence that today’s finance students are future investment analysts whose recommendations drive market mood on a large scale. Notably, this tactic, in every lecture, offered the students not only a reflection on what happens in reality but also significant confidence in how to interpret what they have been introduced to at the beginning of the lecture, including investment news, forecasts, growth rates, etc., the right way objectively.

The five experiments being conducted in this paper are designed to fulfill the ILOs of a standard syllabus of portfolio management at the undergraduate level. Nevertheless, the authors were willing to expand students’ awareness and knowledge beyond the borders of conventional textbooks. The objective is to prepare students to face realities in financial markets. The results conclude that risk attitudes (averse and taking) are well perceived by the students, although the positive association between risk and return is reversed in contrast with the MPT assumption, especially in the foreign currency and metal markets. The results extend those of previous related studies on the effects of overconfidence and biased self-attribution. The experiments revealed an integral understanding of different financial and nonfinancial markets. The latter is usually delivered in separate courses, commonly “Financial Markets and Institutions,” which do not require students to construct investment portfolios. In this case, the students’ understanding of the

“require rate of returns” is widened. The experiments also revealed that participants in financial and nonfinancial markets are not bound by only two risk attitudes. Extended choices are available for investors to choose popular assets, which is referred to in this paper as “availability heuristic.” The latter is associated with mixed degrees of variation (risks), which increase the role of investment advisors, who are actually current finance students. These mixed results offer convenient chances for students to observe the causes and consequences of market anomalies.

The examination of unexpected events, specifically COVID-19, highlighted unobserved reactions in financial markets where a state of uncertainty prevails. In this case, students abandon conventional risk attitudes (aversion and taking) and resort to availability heuristics, which are associated with greater systematic risk (a highly illustrative definition of systematic risk).

The gender effect and home country bias have also materialized. In contrast to female students, male students tend to adopt risk taking. In addition, the highest percentage of preferences is to invest in the home country (Egypt).

Notably, a significant component of experiential learning is receiving students’ feedback. Nearly the end of the semester, and for two lectures in a week, the lecturers opened free discussions, with all the students presenting the final outcomes being reached at the end of the semester. Verbal feedback was received from all the students, without any exception, that they were thrilled by the aggregate outcomes that significantly resembled reality. Notably, experiential learning becomes increasingly informative and challenging with advances in the design of digital games, which must be an integral part of teaching finance courses at large (Yu & Denham, 2021).

Conflict of Interests

The authors declare that they do not have any financial or nonfinancial competing interests that are directly or indirectly related to this paper.

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Appendix

(a): Significance of the risk–return tradeoff across different markets (foreign currencies; metals; common stocks), two-asset portfolio

Mann–Whitney Test		Risk Attitude		Z stat, 2 tail Taking	Bernoulli Indicator Function of Sample Selection Bias [Prob. Risk Averse (Taking)] {Max Likelihood of Risk Averse (Taking)}
		Averse	Taking		
Foreign Currency Portfolio	Variance: N (Mean Rank) (Mean Daily Variance)	22 (11.5) (0.00019%)	37 (41.00) (0.0017%)	-7.616***	1.73472E-18 [37.288% (62.712%)] {10.69% (0.0044%)}
	Return: N (Mean Rank) (Mean Daily Return)	22 (48.5) (-0.015%)	37 (19) (-0.025%)		
Metals Portfolio	Variance: N (Mean Rank) (Mean Daily Variance)	22 (11.5) (0.0078%)	37 (41.00) (0.0103%)	-7.616***	
	Return: N (Mean Rank) (Mean Daily Return)	22 (48.5) (0.0319%)	37 (19) (0.0055%)		
Common Stock Portfolio	Variance: N (Mean Rank) (Mean Daily Variance)	22 (11.5) (0.0186%)	37 (41.00) (0.0241%)	-7.428***	
	Return: N (Mean Rank) (Mean Daily Return)	22 (11.5) (0.0875%)	37 (41.00) (0.1009%)		

*** Significant at the 1% level

(b): Significance of students' understanding of the limits of portfolio diversification

Kruskal–Wallis Test		Portfolio Variance			Portfolio Return		
Assets	Risk Attitude	Averse	Taking	Availability heuristics	Averse	Taking	Availability heuristics
	N	9	23	25	9	23	25
Common Stocks Portfolio	Mean Rank	21.89	26.48	33.88	25.11	25.35	33.76
	Mean	0.003642	0.005208	0.006254	0.023251	0.024189	0.029236
	χ^2 Stat (2 df)	4.345			3.664		
Commodities Portfolio	Mean Rank	9.22	38.00	27.84	21.67	32.96	28.00
	Mean	0.001518	0.005578	0.004665	0.033717	0.039168	0.035126
	χ^2 Stat (2 df)	19.667***			3.155		
Foreign Currencies Portfolio	Mean Rank	16.67	32.96	29.80	32.67	26.70	29.80
	Mean	0.000164	0.000408	0.000505	0.002713	0.001449	0.004203
	χ^2 Stat (2 df)	6.336**			0.941		
Bernoulli Indicator Function of Sample Selection Bias		6.34635E-28					
Prob. Risk (Averse) (Taking)		(28.125%) (71.875%)					
Max Likelihood of Risk (Averse) (Taking)		(15.525%) (0.000031%)					
Prob. Risk (Averse) (Availability heuristics)		(26.471%) (73.529%)					
Max Likelihood of Risk (Averse)(Availability heuristics)		(15.351%) (0.0000012%)					
Prob. Risk (Taking)(Availability heuristics)		(47.917%) (52.083%)					
Max Likelihood of Risk (Taking)(Availability heuristics)		(11.466%) (9.705%)					

(c) Risk Affective Attitudes Before and After COVID-19

Kruskal–Wallis Test		Portfolio of Four Commodities											
		Portfolio Variance			Portfolio Return			R^2 Systematic			R^2 Unsystematic		
		Averse	Availability heuristics	Taking	Averse	Availability heuristics	Taking	Averse	Availability heuristics	Taking	Averse	Availability heuristics	Taking
N		32	12	20	32	12	20	32	12	20	32	12	20
Before COVID19	Mean Rank	27.5	9.17	54.5	17.5	54.17	43.5	20.5	34.5	50.5	44.5	30.5	14.5
	Mean	0.2084%	0.1533%	0.3257%	-1.71%	0.1083%	-1.68%	39.84%	40.12%	44.93%	60.15%	59.88%	55.07%
	Chi Square Stat (2 df)	5.112***			52.100***			38.037***			38.037***		
After COVID19	Mean Rank:	16.5	38.5	34.5	48.5	6.5	22.5	37.5	55.83	10.5	27.5	9.17	54.5
	Mean	0.0337%	0.4255%	1.0305%	1.9469%	0.2613%	0.7233%	69.42%	82.32%	59.34%	30.58%	17.68%	40.66%
	Chi Square Stat (2 df)	62.520***			62.520***			58.112***			58.112***		
Bernoulli Indicator Function of Sample Selection Bias		5.72658E-27											
Prob. Risk (Averse) (Taking)		(61.538%) (38.462%)											
Max Likelihood of Risk (Averse) (Taking)		(11.312%) (0.040%)											
Prob. Risk (Averse) (Availability heuristics)		(72.727%) (27.273%)											
Max Likelihood of Risk (Averse) (Availability heuristics)		(13.401%) (0.000000041%)											
Prob. Risk (Taking)(Availability heuristics)		(62.500%) (37.500%)											
Max Likelihood of Risk (Taking) (Availability heuristics)		(14.443%) (0.242%)											

(d): Testing for Country Selection Bias

#	Country	N	% of Favorable Countries to Invest in	Mean Rank (Portfolio Yield)	Bond Portfolio Weighted Average Yield	Mean Rank (count of chosen countries)
1	Egypt	15	17.44%	75.53	12.306%	37.00
2	Canada	13	15.12%	25.23	2.038%	11.00
3	Greece	5	5.81%	38.80	2.611%	52.00
4	UK	5	5.81%	7.40	0.782%	78.00
5	USA	5	5.81%	40.00	2.470%	84.00
6	China	4	4.65%	45.25	2.635%	22.50
7	Italy	4	4.65%	14.25	1.104%	62.50
8	Chile	3	3.49%	56.00	4.877%	19.00
9	Germany	3	3.49%	8.67	0.807%	48.00
10	Iceland	3	3.49%	52.67	4.209%	59.00
11	Colombia	2	2.33%	65.00	7.813%	25.50
12	Cyprus	2	2.33%	28.50	1.917%	28.50
13	France	2	2.33%	25.00	1.635%	45.50
14	Hungry	2	2.33%	62.50	6.470%	56.50
15	New Zealand	2	2.33%	40.50	2.500%	65.50
16	South Africa	2	2.33%	66.00	8.594%	70.50
17	Turkey	2	2.33%	80.50	13.784%	73.50
18	Australia	1	1.16%	50.00	3.000%	1.00
19	Austria	1	1.16%	59.00	5.500%	2.00
20	Belgium	1	1.16%	7.00	0.854%	3.00
21	Bangladesh	1	1.16%	61.00	5.660%	4.00
22	Croatia	1	1.16%	15.00	1.340%	27.00
23	Hong Kong	1	1.16%	8.00	0.885%	55.00
24	Norway	1	1.16%	36.00	2.430%	67.00
25	Poland	1	1.16%	56.00	5.240%	68.00
26	Qatar	1	1.16%	35.00	2.420%	69.00
27	Spain	1	1.16%	27.00	1.813%	72.00
28	Uganda	1	1.16%	83.00	13.192%	75.00
29	Ukraine	1	1.16%	86.00	37.040%	81.00
		86	100%	$\chi^2 stat(df) = 78.108^{***}$ (28)	$\chi^2 stat(df) = 85.00^{***}$ (28)	

(e): Portfolio Diversification and Risk Preferences: The Gender Effect

Behavioral Attitudes	Test Statistics (Mann–Whitney)	Financial Stocks		Commodities		Foreign Currencies	
		Portfolio Risk	Portfolio Return	Portfolio Risk	Portfolio Return	Portfolio Risk	Portfolio Return
Risk Averse	Z Stat [Asymptotic Significance (2-tailed)] N (Males = 5) (Females = 6)	-1.278 [0.201]	-0.182 [0.855]	-2.378 [0.0173]	-1.829 [0.0672]	-2.190 [0.0284]	-1.0954 [0.273]
	Bernoulli Indicator Function of Sample Selection Bias	0.000488281					
	Prob. Risk Averse (Male) (Female)	(45.455%) (54.545%)					
	Max Likelihood of Risk Averse (Male) (Female)	(23.609%)(19.674%)					
	Mean Rank:						
	Males Females	4.6 7.17	6.20 5.83	3.40 8.166	4.00 7.67	3.6 8	4.8 7
Risk Taking	Z Stat [Asymptotic Significance (2-tailed)] N (Males = 6) (Females = 18)	-0.066 [0.946]	-0.2667 [0.789]	-0.533 [0.5937]	- 0.20004 [0.841]	-1.634 [0.102]	-1.5676 [0.117]
	Bernoulli Indicator Function of Sample Selection Bias	5.96046E-08					
	Prob. Risk Taking (Male) (Female)	(25.000%) (75.000%)					
	Max Likelihood of Risk Taking (Male) (Female)	(18.525%) (0.000035%)					
	Mean Rank:						
	Males Females	12.33 12.555	13.16 12.27	13.833 12.055	13.00 12.333	16.583 11.138	16.41 11.194
Availability heuristics	Z Stat [Asymptotic Significance (2-tailed)] N (Males = 14) (Females = 9)	-0.693 [0.488]	-0.252 [0.801]	-0.756 [0.449]	-1.963 [0.042]	-0.0945 [0.924]	-0.252 [0.8009]
	Bernoulli Indicator Function of Sample Selection Bias	1.19209E-07					
	Prob. availability heuristics (Male) (Female)	(60.870%) (39.130%)					
	Max Likelihood of availability heuristics (Male) (Female)	(16.848%) (1.849%)					
	Mean Rank:						
	Males Females	12.785 10.777	12.28 11.55	12.857 10.666	13.85 9.111	11.89 12.16	11.714 12.44

Empowering Financial Education with AI: Enhancing Student Capabilities in Student-Managed Investment Funds

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This paper examines how advanced AI tools can support students in managing student-managed investment funds (SMIF) by providing them with stronger analytical and visualization capabilities. While these tools do not directly improve fund performance, they enhance students' ability to present data more effectively and make more informed investment decisions. By integrating AI, students can develop deeper insights into asset allocation and risk management, as well as create more impactful visual representations of performance data. My findings suggest that these tools play a crucial role in improving the educational experience, enabling students to better bridge theory and practice. The study highlights the potential for AI to reshape financial education, making it more interactive and effective in preparing students for real-world financial challenges.

Keywords: Artificial Intelligence in Finance, Financial Education, Student-Managed Investment Fund (SMIF), Asset Allocation, Finance Pedagogy

JEL Codes: G11, G12, C88, I21, O33, A22

Introduction

Valparaiso University's Student-Managed Investment Fund (SMIF) is managed through the Portfolio Practicum course, a 3-credit hour class where students actively oversee a portfolio valued at \$800,000, funded by alumni donations. This hands-on course provides students with real-world investment experience, making strategic decisions on stock selection, asset allocation, and risk management. Students lead the fund under the supervision of faculty advisors, integrating both traditional financial analysis and AI-driven tools. Throughout the course, they are required to submit monthly reports that monitor and assess their stock selections and portfolio performance. The fund's performance is reviewed and reassessed annually, ensuring continuous learning and improvement. The course prepares students for careers in asset management, investment banking, and financial analysis by giving them direct experience in managing a live portfolio and refining their investment strategies.

The growing use of artificial intelligence (AI) in financial education has introduced a range of new tools and applications that are transforming how students learn and apply financial concepts. Traditionally, financial education relied on established platforms like Bloomberg Terminal ([Lei & Li, 2012](#)) and financial statement analysis, which provided students with a solid foundation but required significant human interpretation and effort. However, the rise of AI tools has introduced automation, real-time predictive analytics, and enhanced visualization capabilities ([Javaid, 2024](#)), offering students more powerful and adaptive resources to manage and analyze data. AI has been successfully integrated into educational contexts, helping students engage with adaptive learning feedback systems ([Heffernan & Heffernan, 2014](#)), and immersive learning environments, thereby enhancing the learning experience across various subjects ([Zhai et al., 2021](#)). Similarly, AI holds transformative potential in augmenting human cognition in learning, offering individualized

instruction and automating complex problem-solving tasks ([Holmes et al., 2019](#); [Holmes & Tuomi, 2022](#)). These advancements suggest a promising future for AI-driven financial education, where students are empowered to focus more on decision-making and strategic thinking in real-world market scenarios. This study seeks to explore the impact of integrating AI tools into student-managed investment funds (SMIF) and how they compare to traditional finance tools in enhancing students' analytical and presentation skills.

Student-Managed Investment Funds (SMIF) provide invaluable hands-on experience for students to apply financial theories in real-world scenarios. However, the utilization of traditional finance tools within SMIF presents several challenges that can hinder effective learning and performance. Traditional tools such as Bloomberg Terminals and Excel-based models, while robust, require substantial time investment for data manipulation and analysis, limiting students' ability to focus on strategic decision-making ([Lei & Li, 2012](#)). Additionally, these tools often lack the flexibility and adaptability needed to accommodate the dynamic nature of financial markets, making it difficult for students to respond swiftly to market changes. The steep learning curve associated with mastering these traditional platforms can also be a barrier, particularly for students with limited technical backgrounds, potentially leading to frustration and disengagement. Moreover, the manual processes involved in data analysis increase the risk of errors, which can adversely affect investment decisions and outcomes ([Zhao et al., 2024](#)). These challenges highlight the necessity for integrating more advanced AI-driven applications into SMIF. AI tools can automate data processing, provide real-time predictive analytics, and offer personalized feedback, thereby enhancing students' analytical capabilities and allowing them to concentrate on higher-level strategic thinking ([Holmes et al., 2019](#); [Sajja et al., 2023](#)). By leveraging AI, SMIF programs can offer a more efficient, accurate, and engaging learning environment, ultimately improving educational outcomes and better preparing students for careers in finance ([Javaid, 2024](#)).

The primary objective of this study is to evaluate the effectiveness of artificial intelligence (AI) tools compared to traditional financial tools in enhancing students' abilities to analyze and present the performance of Student-Managed Investment Funds (SMIF). Specifically, the research aims to assess whether AI-driven applications provide superior analytical capabilities, improve the accuracy of financial assessments, and facilitate more effective presentations of investment outcomes compared to conventional tools like Bloomberg Terminals and Excel-based models ([Lei & Li, 2012](#)). Additionally, the study seeks to determine the extent to which AI tools can streamline data processing, offer insights, and support decision-making processes, thereby allowing students to focus more on strategic analysis and presentation skills ([Zhai et al., 2021](#)). By conducting comparative analysis, this research intends to identify the specific advantages and potential limitations of integrating AI technologies into SMIF programs, ultimately providing recommendations for educators and program administrators to enhance financial education through technological innovation. The findings of this study are expected to contribute to a broader understanding of how AI can be leveraged to improve educational outcomes in finance-related disciplines.

This study aims to investigate the comparative effectiveness of artificial intelligence (AI) tools versus traditional financial tools in the context of Student-Managed Investment Funds (SMIF). Specifically, the research seeks to answer how AI tools enhance student learning outcomes compared to traditional platforms, addressing the question: How do AI tools compare with traditional tools in enhancing student learning outcomes in SMIF? Previous studies have highlighted the potential of AI to provide personalized learning experiences and advanced analytical capabilities ([Holmes et al., 2019](#)). Additionally, the study explores the impact of AI-

driven tools on the visualization and interpretation of SMIF performance data, posing the question: What impact do AI-driven tools have on the visualization and interpretation of SMIF performance data? Enhanced data visualization through AI can lead to more intuitive and actionable financial insights (Zhai et al., 2021). Furthermore, the research examines the extent to which AI tools improve students' analytical and presentation skills compared to traditional methods, asking: To what extent do AI tools improve students' analytical and presentation skills in managing SMIF compared to traditional tools? AI's ability to automate complex data processing and provide real-time feedback is expected to significantly enhance these skills (Javaid, 2024). The study also seeks to understand the perceived challenges and benefits of integrating AI tools from the students' perspective, addressing: What are the perceived challenges and benefits of integrating AI tools into SMIF from the students' perspective? Insights into student experiences are crucial for successful AI implementation in educational settings (Heffernan & Heffernan, 2014). By addressing these questions, the study aims to provide a comprehensive understanding of AI's role in enhancing financial education through SMIF, ultimately offering evidence-based recommendations for educators and program administrators.

While AI tools significantly improve the processes of analysis and presentation, they may not directly translate to enhanced overall performance of the SMIF. Factors such as market volatility, student decision-making skills, and external economic conditions play roles in determining the fund's performance, which are beyond the direct influence of AI tools (Yi et al., 2023). Additionally, the effectiveness of AI integration is contingent upon the students' proficiency in utilizing these technologies and the quality of the AI tools themselves, which may vary across different educational settings (How et al., 2020). Therefore, while AI tools offer valuable enhancements to the analytical and presentation aspects of SMIF, their impact on overall fund performance remains mediated by a combination of technological, educational, and market-related factors.

Literature Review

The Role of AI in Finance

Artificial Intelligence (AI) has significantly influenced the financial industry, automating complex processes, improving decision-making, and providing valuable insights from large datasets. This review examines AI's growing applications in both financial analysis and education, reflecting the importance of AI tools in shaping the future of finance.

AI's role in risk management is equally transformative. Machine learning models are applied to assess and mitigate financial risks, leveraging historical and real-time data to predict and avert potential risks. These models analyze large sets of financial and non-financial data, such as credit histories, market behaviors, and economic conditions, enabling firms to forecast credit risks, market fluctuations, and operational risks more effectively (Metawa et al., 2022). The ability to anticipate these risks with higher accuracy has led to improvements in the way banks and financial institutions manage their portfolios and credit decisions (Frey & Embrechts, 2010).

AI has also proven valuable in sentiment analysis, where natural language processing (NLP) tools analyze market sentiment by processing unstructured data from diverse sources, including news articles, social media platforms, and company reports. By examining the tone, context, and frequency of keywords, AI can gauge public sentiment around specific stocks or markets, offering actionable insights for investors and analysts (Nti et al., 2020). The ability to synthesize such

information in real-time gives firms a competitive edge, as they can quickly respond to emerging trends or potential risks.

AI-driven algorithmic trading systems utilize complex algorithms and machine learning models to execute trades at optimal times, often outperforming human traders in speed and accuracy. These systems analyze vast amounts of market data, identify patterns, and make real-time trading decisions, thereby maximizing returns and minimizing risks ([Hendershott et al., 2011](#)). In portfolio management, AI assists in asset allocation, diversification, and rebalancing by continuously assessing market conditions and adjusting portfolios to align with investors' risk preferences and financial goals ([Hendershott et al., 2009](#)). Robo-advisors, powered by AI, have democratized access to sophisticated investment strategies, making personalized financial advice available to a broader audience at a lower cost ([Lam et al., 2016](#)).

In the realm of financial education, AI plays a pivotal role in creating personalized learning experiences and interactive training modules ([Hashim et al., 2022](#)). AI-driven platforms can assess learners' knowledge levels, adapt content to their learning pace, and provide targeted feedback, thereby enhancing the effectiveness of financial education programs ([Hendershott et al., 2011](#)). Virtual simulations and gamified learning environments enable users to practice financial decision-making in a risk-free setting, fostering a deeper understanding of complex financial concepts. Furthermore, AI facilitates the creation of intelligent tutoring systems that offer real-time assistance and support, making financial education more engaging and accessible to a diverse audience.

Traditional Finance Tools in Financial Education

The use of traditional finance tools, such as Bloomberg Terminal, Yahoo Finance, Value Line, and financial news platforms, is integral to modern financial education. These tools provide market data, analytics, and insights, enabling students to engage with financial concepts in practical, real-world contexts. This review focuses on the significance of these tools and their roles in enhancing student learning.

Bloomberg Terminal remains one of the most comprehensive tools used in finance education, offering access to real-time data on a wide range of financial instruments such as stocks, bonds, currencies, and commodities ([Sharma, 2015](#)). Its advanced analytics and data visualization capabilities allow students to explore financial scenarios, analyze market trends, and simulate trading environments, which enhances their practical understanding of financial concepts ([Sharma et al., 2018](#)). Bloomberg Terminal's use in academic settings bridges the gap between classroom theories and professional practice, offering students the opportunity to develop technical skills directly applicable in the workforce ([Adhikari & Ionici, 2022](#)).

Bloomberg's detailed access to company financials, news, and economic data allows for a deeper engagement with market mechanics, while its tools for scenario modeling and financial forecasting prepare students for high-level decision-making in real-world financial markets ([Moreale & Zaynutdinova, 2018](#)). In addition, the ability to access Bloomberg Terminal enhances the research capabilities of students, allowing them to apply academic theories to real-time financial data ([Abramov et al., 2015](#)).

In traditional financial education, the Value Line is commonly used to teach students fundamental aspects of equity valuation and investment analysis. It provides comprehensive data on stocks, mutual funds, and various sectors, allowing educators to integrate practical examples into classroom discussions. The Value Line's timeliness and safety ranking system has been especially valuable for helping students assess stock performance, risk factors, and market timing.

Research supports its pedagogical value in bridging the gap between theoretical finance concepts and real-world applications. For instance, Baird (2013) illustrates how the Value Line can be used as a teaching template for equity valuation, offering a structured approach to analyzing financial statements, forecasting earnings, and evaluating growth potential. The use of Value Line data enables students to apply theories like portfolio diversification and equity valuation using live market data, enhancing the practical understanding of investment strategies and risk management.

This tool has consistently been regarded as an effective educational resource in financial courses, supporting experiential learning through data-driven analysis and fostering critical thinking among students in finance programs (Baird, 2013; Chen 2003).

In finance education, visualization tools play a critical role in helping students understand complex financial data and investment performance. Performance visualization tools enable students to analyze trends, patterns, and anomalies in real-time, making abstract concepts more accessible and fostering a deeper understanding of market dynamics.

Studies have shown that integrating technologies such as interactive dashboards, charting software, and AI-driven analytics platforms enhances the learning experience by making data more interpretable (Clark & Mayer, 2023). Tools like Bloomberg Terminals and Tableau have become common in finance programs, allowing students to visualize stock movements, fund performance, and portfolio composition through interactive graphs and models. These visual aids improve cognitive retention and support practical applications of theoretical finance principles.

Moreover, new advancements in financial technologies, including AI and machine learning, offer even more sophisticated visualization techniques. AI-powered tools can automatically generate insights and performance predictions based on historical data, further enhancing students' ability to forecast market trends and assess risk (Xiao & Zhao, 2017). These tools not only improve comprehension but also prepare students for the increasingly data-driven nature of the financial industry.

Comparing AI Tools and Traditional Finance Tools

The Bloomberg Terminal has long been recognized as a cornerstone of the financial industry, offering unparalleled access to real-time market data, analytics, and news. Traditionally utilized by professionals in investment banking, portfolio management, and financial research, the Terminal has also become a pivotal tool in financial education. As universities increasingly integrate practical tools into their curricula, the Bloomberg Terminal stands out as a vital resource for bridging the gap between academic learning and industry practice.

Since its introduction in 1981, the Bloomberg Terminal has revolutionized financial markets by providing instant access to vast amounts of market data. However, the Terminal's value extends beyond market professionals; its utility in academic settings has grown as universities have adopted it as a means of delivering real-world experience to students. The integration of the Terminal into classroom instruction and research projects allows students to gain practical exposure to financial data, often unavailable through traditional academic methods.

Through Bloomberg for Education, students are not just introduced to financial theories but are also immersed in real-world financial markets via the Bloomberg Terminal. This access provides invaluable experience in navigating the complexities of market dynamics, financial analytics, and industry-specific data, all of which are critical to succeeding in finance-related careers. Furthermore, Bloomberg for Education offers a dedicated Education Portal, where students can explore an extensive range of resources, including CPD-accredited certificate courses,

interactive simulations, webinars, and case studies designed to deepen their understanding of global financial systems.

Table 1
Comparison of Bloomberg Finance Fundamentals, Bloomberg Market Concepts, and ESG Certificates

	Bloomberg Finance Fundamentals (BFF)	Bloomberg Market Concepts (BMC)	Environmental Social Governance (ESG)
Type of Course	Self-paced, interactive e-learning course	Self-paced, interactive e-learning course	Self-paced, interactive e-learning course
Primary Focus	Introduction to finance and investment concepts	In-depth exploration of financial markets	ESG strategies and reporting for asset management
Key Learning	<ul style="list-style-type: none"> - Money flow in the economy - Investment strategies - Responsible investing - Career exploration 	<ul style="list-style-type: none"> - Financial markets - Economic indicators - Currencies - Fixed income - Equities - Commodities 	<ul style="list-style-type: none"> - ESG trends and investment strategies - ESG integration fixed income/equities - Corporate governance and activism
Target Audience	Beginners in finance and investment	Individuals looking to strengthen their knowledge of financial markets	Learners interested in ESG reporting and sustainable finance
Certification Modules	Available after core modules <ul style="list-style-type: none"> - Purpose of Investing - Types of Investment - Risk and Reward - Portfolio Management 	Available after core modules <ul style="list-style-type: none"> - Economic Indicators - Currencies - Fixed Income - Equities - Commodities - Equity Options - Portfolio Management 	Available after core modules <ul style="list-style-type: none"> - Introduction to ESG - Researching and Adopting ESG - Negative & Positive Screening - ESG Integration - Corporate Governance
Skills Developed	Basic finance understanding, responsible investing, portfolio management	Financial market knowledge, Bloomberg Terminal functions, analysis of equities, fixed income, and currencies	ESG integration, reporting, responsible investing, corporate governance, shareholder activism
Flexibility	100% online, self-paced	100% online, self-paced	100% online, self-paced
Tools Used	Basic finance concepts and career tools	Over 150 Bloomberg Terminal functions	ESG strategies and reporting tools
Duration	Self-paced	Self-paced	Self-paced

Table 1 presents a comparison of three Bloomberg certificates—Bloomberg Finance Fundamentals (BFF), Bloomberg Market Concepts (BMC), and Environmental Social Governance (ESG). These certifications, with varying areas of focus, allow students to develop foundational knowledge in finance, deepen their understanding of financial markets, and learn about ESG investment strategies, ultimately enhancing their preparedness for careers in finance.

One of the key components of this program is the Bloomberg Market Concepts (BMC) course, which certifies students in Bloomberg Terminal proficiency and core financial concepts such as equities, fixed income, and currencies. This certification not only equips students with practical technical skills but also enhances their career prospects by providing them with a credential widely recognized and valued by employers in the financial sector. Beyond universities, many high schools and learning institutions globally are also integrating Bloomberg for Education into their curriculum, ensuring that students from various academic levels can benefit from these hands-on, market-driven learning experiences.

Moreover, the Terminal plays a crucial role in Student Managed Investment Funds (SMIF), where students manage actual or simulated portfolios. By utilizing Bloomberg's tools, students evaluate securities, monitor market conditions, and make informed investment decisions. The certificate programs further enhance these experiential learning opportunities by equipping students with recognized credentials and in-depth financial knowledge, which helps them effectively apply theoretical concepts in practice. This combination of certifications and hands-on portfolio management experience allows students to gain a comprehensive understanding of market dynamics and portfolio management strategies, making them more competitive in the job market.

Despite its numerous advantages, the use of the Bloomberg Terminal in academic settings presents challenges. The most significant is the cost of the Terminal, which can be prohibitive for smaller institutions or those with limited budgets. Larger universities may offer multiple Bloomberg Terminals in dedicated finance labs, but smaller institutions might struggle to provide adequate access for all students. Another challenge is the learning curve associated with the Bloomberg Terminal. The platform's comprehensive nature, while beneficial for advanced users, can overwhelm students unfamiliar with its functions. Thus, educators must allocate time and resources to train students in using the Terminal effectively. Institutions that successfully integrate Bloomberg typically offer supplementary workshops or tutorials to help students master the platform.

The educational benefits of using Bloomberg are evident. Students proficient in the Terminal not only develop practical skills but also gain a deeper understanding of market mechanisms, financial modeling, and investment strategies. These skills are highly sought after by employers, making Bloomberg proficiency a significant advantage for graduates entering the financial sector. Bloomberg Education offers a flexible structure, allowing educators to tailor content like ESG, Fintech, and AI & Data Science to suit their course objectives. This flexibility ensures that students not only master traditional finance skills but also stay up to date with evolving industry trends, providing a comprehensive, modern financial education.

Table 2
Key Differences Between FinChat (AI Tool) and Bloomberg (Traditional Tool)

Feature	FinChat (AI Tool)	Bloomberg (Traditional Tool)
Data Processing	Processes large datasets quickly, finds hidden patterns automatically.	Relies on user expertise to navigate and interpret large datasets manually.
Predictive vs. Historical Analysis	Offers predictive models using AI for forecasting.	Focuses on historical data analysis, leaving forecasting to user discretion.
Automation	Automate tasks like portfolio management and risk assessments.	Manual processes for tasks like portfolio management and risk assessments.
Personalization and Adaptability	Allows personalized queries and customizable outputs for specific analysis.	More static and generalized, with less emphasis on real-time customization.
Cost	It is more affordable or accessible for students and institutions.	High subscription cost, often a barrier for smaller institutions or individuals.
User Interface and Learning Curve	User-friendly and intuitive, AI simplifies complex tasks and queries.	Complex interface with a steep learning curve, requiring training.
Collaboration and Sharing	Supports easy collaboration and sharing of results or custom queries.	Collaboration is manual, requiring export or manual sharing of findings.
Integration with Learning Platforms	Offers blog resources for learning fundamental analysis.	Provides Bloomberg Education and certification programs for students.

The emergence of OpenAI has marked a revolutionary shift in how artificial intelligence is integrated into various industries, and the world of investment education is no exception. With the advent of advanced AI, platforms like FinChat (Seen in Table 2) have been developed to reshape how students learn about investment, providing them with cutting-edge tools that enhance both their understanding and practical skills in finance.

FinChat, as a specialized platform, is designed to offer students a unique opportunity to experience investment management in a way that mimics real-world scenarios. For students in programs like Student Managed Investment Funds (SMIF), FinChat’s ability to visualize financial data is transformative. It enables students to generate real-time charts, compare companies, and see the direct impact of market trends through intuitive visual interfaces. This not only helps them understand the abstract financial concepts more clearly but also improves their ability to interpret financial data briefly.

Moreover, FinChat goes beyond basic visualization by offering robust tools for individual stock research. Students can dive deep into company-specific financials, segment data, and key performance indicators (KPIs) that would typically be available only to seasoned analysts. With access to 20 years of historical data and up-to-date financial metrics, students can assess how different stocks have performed over time, helping them make informed decisions about which stocks to include in their portfolios.

Another significant feature of FinChat is its support for portfolio construction. Students can use the platform to simulate and build diversified portfolios, experimenting with asset allocation strategies that align with their investment goals. Whether they are building equity portfolios or

researching fixed-income instruments, FinChat provides a comprehensive set of tools that help students balance risk and return, preparing them for real-world fund management roles.

In addition to individual stock analysis and portfolio construction, FinChat offers an ETF database, which allows students to explore exchange-traded funds and understand how ETFs fit into broader investment strategies. The database provides insights into ETF holdings, performance metrics, and expense ratios, giving students the ability to incorporate ETFs into their portfolio strategies for broader diversification or specific sector exposure.

Figure 1
FinChat Copilot Function Displaying Query and Response Process

Figure 1a. Summary Generated by FinChat Copilot in Response to User Query

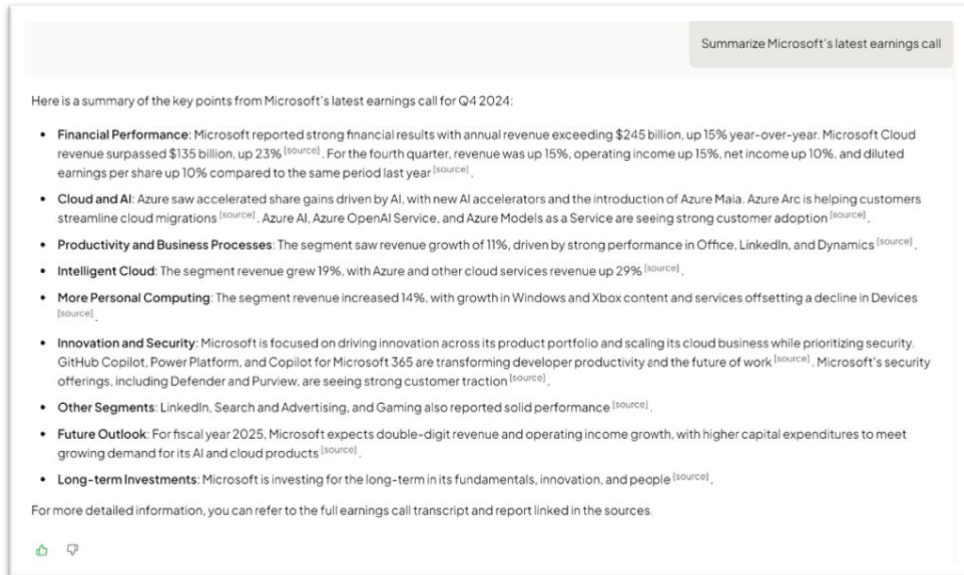
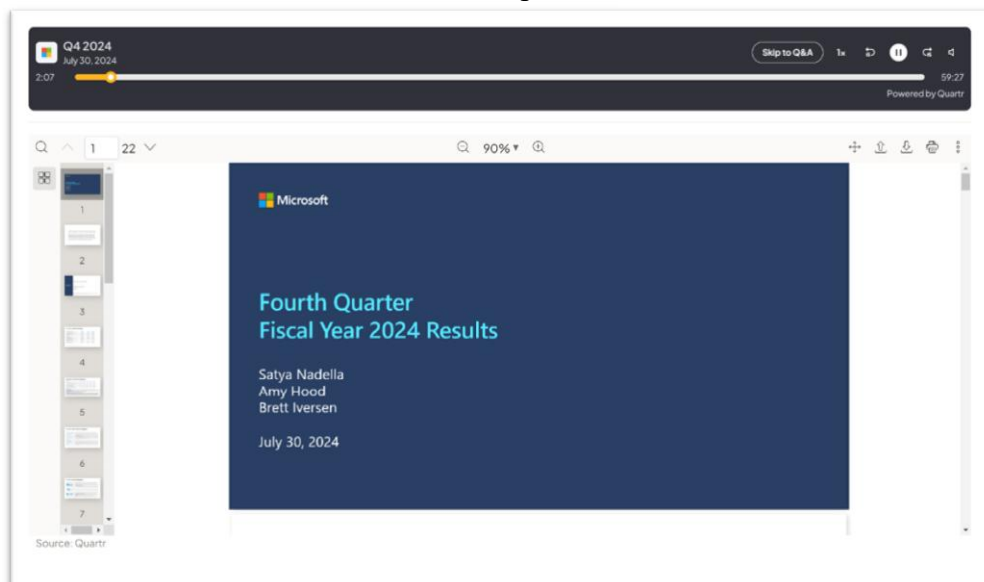


Figure 1b. FinChat Copilot Result Displaying Conference Slides, Full Transcript, Audio Files, and Report



One of the most powerful features of FinChat is the Copilot—an AI assistant built specifically for financial research. Copilot allows students to query the platform directly, enabling them to quickly access information without the need to navigate through multiple screens or complex data sets. For example, students can use simple prompts like “Summarize Microsoft’s latest earnings call” or “List the top 10 dividend-paying stocks” to get immediate, actionable insights. As shown in Figure 1, Copilot not only provides a summary of the requested information but also offers access to additional resources like conference slides, transcripts, and reports, streamlining the research process and enhancing the overall learning experience. This not only saves time but also enhances the learning experience by allowing students to focus more on analysis and strategy rather than on data collection.

Shortly, from OpenAI’s initial breakthrough to FinChat’s impactful role in investment education, AI is profoundly changing the way students approach finance. FinChat’s ability to visualize data, conduct in-depth stock research, assist in portfolio construction, provide ETF insights, and interact through its Copilot AI assistant makes it an indispensable tool for today’s finance students. The platform ensures that they gain both the theoretical knowledge and practical skills necessary to succeed in the fast-paced world of investment management.

Key Differences Between AI Tools and Traditional Tools

The rapid development of artificial intelligence (AI) tools has significantly transformed financial data analysis, particularly when comparing modern AI-driven platforms such as FinChat to traditional tools like Bloomberg. One key distinction lies in functionality and automation. FinChat automates various complex tasks, including portfolio management, risk assessments, and data analysis. By processing large datasets and identifying hidden patterns autonomously, FinChat allows users to gain valuable insights without needing extensive manual intervention. This is in contrast to Bloomberg, which, while equally powerful, requires users to manually navigate its platform, analyze datasets, and interpret results based on their own expertise. For example, while a FinChat user might receive portfolio optimization suggestions through an automated process, a Bloomberg user would need to manually configure data filters and generate reports to reach similar outcomes.

Customization and flexibility further differentiate these two tools. FinChat’s AI capabilities allow for personalization based on user interaction, enabling it to adapt to individual preferences and evolve with continued use. This flexibility results in more tailored outputs, where FinChat refines its analysis and recommendations according to past user behavior. Bloomberg, on the other hand, provides customization through predefined settings and manual configuration. However, without any learning capability, it does not adapt based on user preferences, thus requiring a more hands-on approach to extract the desired information.

In terms of data handling and scalability, FinChat excels at processing large volumes of data in a highly efficient manner. It can quickly identify trends and patterns across extensive datasets, making it an ideal tool for users dealing with complex and sizable portfolios. Bloomberg, while capable of handling significant amounts of data, relies heavily on the user's expertise to manage, process, and analyze it manually. This often makes Bloomberg less accessible for those without advanced financial expertise or the time to engage in intricate data interpretation.

Another essential difference is learning and evolution. FinChat, as an AI tool, continuously learns from user interactions, enhancing its accuracy and relevance over time. This evolving nature allows it to provide progressively refined recommendations, particularly in dynamic financial

environments where user needs and market conditions are constantly changing. Bloomberg, in contrast, is static in this regard; its functionality remains fixed unless manually updated by the user or through periodic software updates. It does not improve its performance or adapt to user behavior in the same manner as AI-driven tools.

Finally, the user interaction and interface also highlight the divergence between AI tools like FinChat and traditional platforms like Bloomberg. FinChat's intuitive, user-friendly design supports natural language processing, allowing users to input queries in everyday language and receive actionable insights with minimal effort. This ease of interaction makes FinChat accessible to users with varying levels of financial expertise, fostering more efficient collaboration and sharing of results. On the other hand, Bloomberg, though a robust platform, requires a steep learning curve to navigate its complex interface, making it more suited for financial professionals. Collaboration within Bloomberg is largely manual, requiring users to export data or reports for external sharing, which contrasts with the seamless sharing capabilities that FinChat offers through its modern interface.

Impact on Financial Education

The integration of AI tools into financial education, especially for Student Managed Investment Funds (SMIF), transforms both analytical and communication aspects of student learning. By automating complex tasks like data processing, coding, and regression analysis, AI tools allow students to focus more on strategic decision-making. This not only saves time but also enables students to dig deeper into investment strategies, such as evaluating risk-adjusted performance and exploring "what-if" scenarios, leading to more optimal decisions.

Moreover, the enhanced ability to visualize and present fund performance through interactive dashboards and real-time data analysis improves students' communication skills. AI tools provide polished, professional reports that make complex financial data easier to interpret. As a result, students can communicate their insights more clearly and effectively to stakeholders, such as university boards or potential investors. The combination of more time for decision-making and improved presentation capabilities bridges the gap between theoretical finance and practical application, helping students develop both their analytical and communication skills—key competencies for real-world financial management.

Methodology

The data for this study is derived from the Student Managed Investment Fund (SMIF) at Valparaiso University, spanning the academic years [2024-2025]. Throughout this period, students actively participated in managing the fund, taking on responsibilities such as portfolio construction, asset allocation, stock selection, and performance evaluation. These tasks were carried out under the guidance of faculty advisors, with students making decisions based on both fundamental and technical analyses. The SMIF data includes detailed records of all transactions, asset allocations, and portfolio performance metrics, along with student-prepared reports and presentations. This data provides a comprehensive view of the fund's management and serves as the foundation for analyzing how different tools (AI-driven and traditional platforms) impacted the students' decision-making, learning outcomes, and presentation skills.

While SMIF data, such as transaction records and performance reports, offer contextual support, the questionnaire enables a more nuanced understanding of how these tools specifically

affect the students' learning processes. The responses will offer insights into how each tool enhances or impairs students' ability to analyze portfolios, make timely investment decisions, and communicate their findings effectively. In this way, the questionnaire serves as the most effective method to capture the subjective dimensions of student learning that cannot be fully explained through performance data alone.

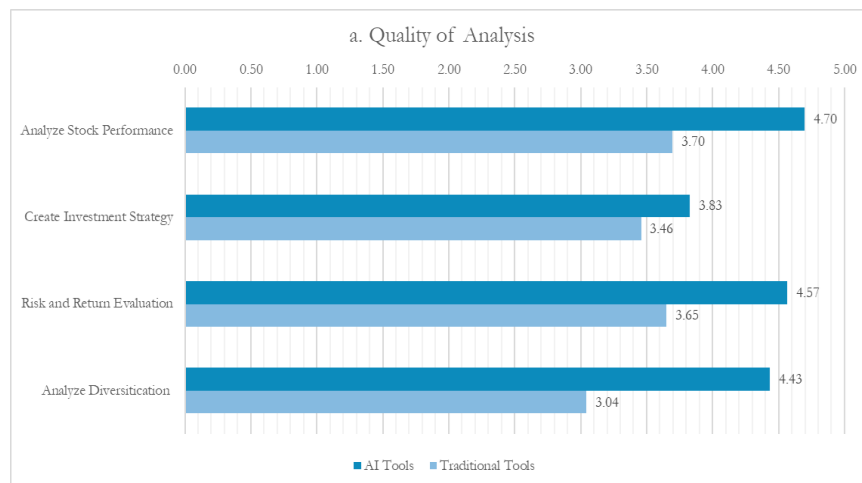
In support of this analysis, survey data were collected from 23 students enrolled in the SMIF program during the 2024–2025 academic year. Participants were drawn from two upper-level finance courses: FIN-420 (Investment Management) and FIN-435 (Portfolio Practicum). The questionnaire was administered online via Google Forms during the final two weeks of the semester. Participation was voluntary but not anonymous, and all students provided informed consent to have their responses linked to their coursework for instructional evaluation purposes. The questionnaire is designed to evaluate the following key areas: (See the Appendix for the full list of questions and results)

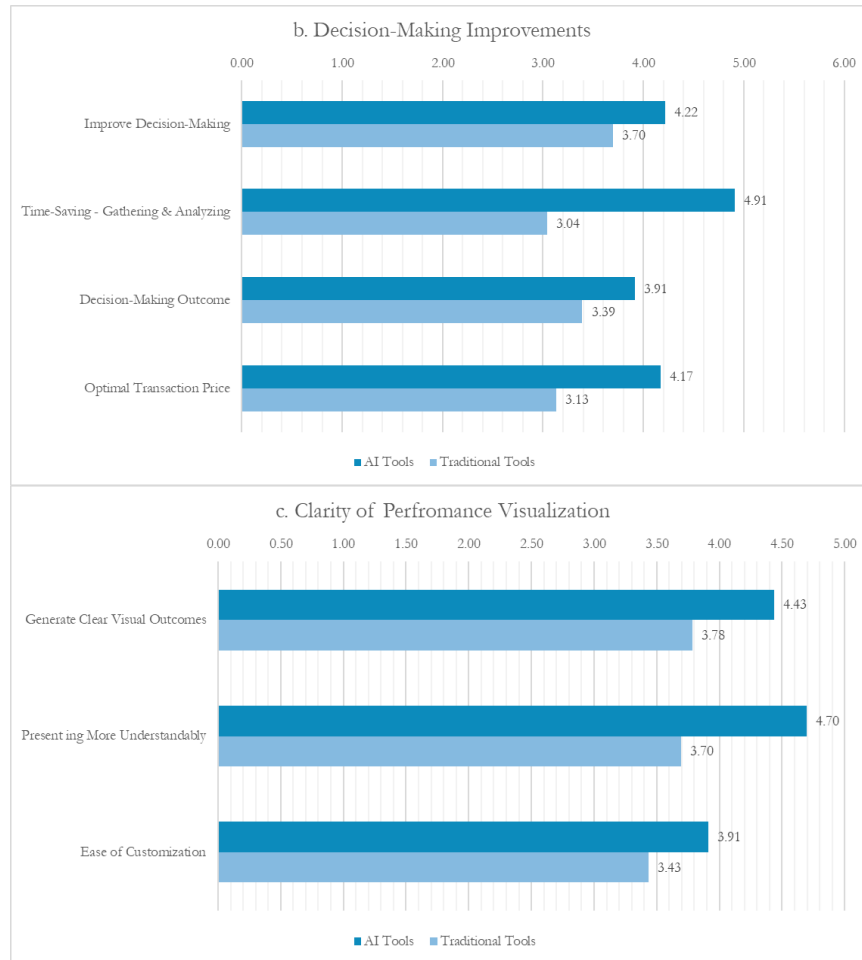
- Quality of analysis: The ability of students to develop comprehensive, accurate, and insightful investment strategies.
- Decision-making improvements: The impact of each tool on students' confidence, speed, and accuracy in making investment decisions.
- Clarity of performance visualization: The effectiveness of the tools in helping students present portfolio performance clearly and professionally.

By focusing on these criteria, the study aims to assess how AI tools and traditional platforms influence student learning outcomes, particularly in the areas of analysis, decision-making, and presentation skills.

Findings and Discussions

Figure 2
A Comparative Analysis of AI and Traditional Tools in Financial Education (From Questionnaires): I. Quality of Analysis, II. Decision-Making Improvements, and III. Clarity of Performance Visualization.





Analytical Depth and Effectiveness

This section evaluates students' perceptions of how AI and traditional tools supported their analytical tasks, including stock performance analysis, risk-return evaluation, investment strategy creation, and diversification analysis.

Figure 2.a presents the average scores for each task under AI and traditional tools, based on student ratings: (1.) Stock Performance Analysis: Students rated AI tools higher (4.70, SD = 0.62) than traditional tools (3.70, SD = 1.20), indicating a perceived advantage of AI in handling large datasets and delivering real-time insights. (2.) Risk and Return Evaluation: AI tools received a mean student rating of 4.57 (SD = 0.77), compared to 3.65 (SD = 1.09) for traditional tools, suggesting that students found AI more helpful for evaluating risk-adjusted returns. (3.) Investment Strategy Creation: Student ratings for AI tools averaged 3.83 (SD = 1.24), slightly higher than traditional tools at 3.46 (SD = 1.08), reflecting moderate perceived effectiveness in strategic planning tasks. (4.) Diversification Analysis: AI tools were rated at 4.43 (SD = 0.79), while traditional tools received 3.04 (SD = 1.14), indicating a stronger perceived ability of AI to help visualize sector and asset class distributions.

These results reflect student perceptions of AI's benefits in data-driven analytical tasks. However, it is important to note that these scores are based on subjective evaluations rather than direct assessments of analytical performance.

Decision-Making Improvements

This section explores how students perceived the support of AI and traditional tools in decision-making areas, including optimizing transaction prices, saving time, and increasing confidence.

As shown in Figure 2.b: (1.) Timesaving: AI tools received the highest student rating (4.91, SD = 0.29) compared to traditional tools (3.04, SD = 1.00), indicating a strong perception of efficiency gains. (2.) Decision-Making Confidence: Students rated AI tools at 4.22 (SD = 0.88), slightly higher than traditional tools (3.70, SD = 1.01), suggesting that AI was seen as providing more reliable support. (3.) Decision-Making Outcomes: The perceived benefit of AI was narrower (3.91, SD = 1.05) versus traditional tools (3.39, SD = 1.05), implying mixed views on actual impact. (4.) Transaction Price Optimization: AI tools received a higher perceived effectiveness score (4.17, SD = 0.83) than traditional tools (3.13, SD = 1.14).

Again, while these findings illustrate positive student sentiment toward AI integration, they do not represent objectively verified improvements in decision quality.

Clarity of Performance Visualization

This section examines how students perceived the clarity and customizability of visual outputs generated using AI and traditional tools.

Figure 2.c highlights the following results: (1.) Generating Clear Visuals: AI tools were rated at 4.43 (SD = 0.84), surpassing traditional tools at 3.78 (SD = 0.95), showing a perceived improvement in visual clarity. (2.) Presenting Understandably: Students rated AI tools higher (4.70, SD = 0.75) than traditional tools (3.70, SD = 1.01), suggesting that AI supported more effective communication. (3.) Ease of Customization: The difference was smaller, with AI rated at 3.91 (SD = 0.87) and traditional tools at 3.43 (SD = 1.07), reflecting comparable levels of perceived flexibility.

While students consistently rated AI tools more favorably in visualization tasks, it is essential to emphasize that these assessments are based on their self-reported impressions, not externally validated outputs.

AI tools significantly improve clarity and presentation quality, which are critical for financial reporting. However, the smaller gap in customization suggests that traditional tools may still meet students' needs for basic reporting tasks.

The students' responses highlight a nuanced perception of AI and traditional tools. While AI tools were highly rated for their perceived speed, precision, and clarity, students still expressed a preference for traditional tools in tasks requiring validation, autonomy, and interpretive flexibility. This dual reliance reflects a learning environment where both technologies are viewed as complementary, each offering distinct strengths that align with different phases of financial analysis and decision-making. These findings, while based on subjective evaluations, underscore the importance of integrating both toolsets to enhance the overall educational experience.

Challenges and Limitations of AI Integration

Although students generally expressed positive perceptions of AI tools, several reported challenges associated with their use, reflecting a more nuanced experience. For example, some students noted a steep learning curve when first engaging with AI-driven interfaces, especially those unfamiliar with natural language prompts or data modeling syntax. One student commented that “the AI sometimes gave answers that looked polished but were hard to verify, making it difficult to know whether I could fully trust the output.”

Others pointed out that while AI saved time on data gathering, it sometimes oversimplified complex investment contexts, limiting the depth of learning in certain scenarios. A few also mentioned that overreliance on AI led to reduced engagement with manual analysis, especially in risk assessment or valuation modeling, which could be problematic in skill retention over time.

These perceived challenges underline the importance of integrating AI tools in a pedagogically structured way—one that includes critical discussion, transparency of output, and cross-validation with traditional methods. This balance can prevent students from treating AI as a black box and instead promote reflective, informed use.

Refined Practical Applications for Educators

The findings of this study point to several pedagogically informed approaches that may enhance the integration of AI and traditional tools in finance education. Rather than displacing conventional platforms such as Excel or Bloomberg, AI tools appear most effective when introduced progressively beginning with tasks like data visualization and trend identification, and advancing to areas such as forecasting or portfolio optimization as students develop familiarity and confidence.

Learning activities that encourage students to complete comparable tasks using both AI and traditional tools, followed by guided reflection, may deepen their understanding of the relative strengths and limitations of each approach. Such assignments foster not only technical fluency but also critical evaluation skills.

Collaborative projects, such as case-based simulations, can offer further value by requiring students to decide when and how to deploy AI tools within a team-based analytical process. Additionally, brief instructional modules on AI prompting, interpretation, and validation techniques can help students engage with these technologies more responsibly.

Taken together, these practices align with the broader goal of preparing students to navigate a financial industry increasingly shaped by automation, while maintaining the depth of judgment and analytical rigor that traditional methods cultivate.

Conclusion and Future Research

In conclusion, the findings of this study demonstrate that AI tools significantly enhance students’ ability to analyze data, make informed decisions, and effectively present their findings in financial education settings. These tools streamline data processing, generate real-time insights, and support dynamic visualization—capabilities that empower students to focus more on strategic judgment rather than manual tasks. However, the results also highlight areas where traditional tools remain competitive, particularly in tasks requiring interpretive flexibility, industry familiarity, or hands-on modeling. This suggests a complementary instructional approach, where AI tools and

traditional platforms such as Bloomberg Terminals and Excel are integrated to maximize learning outcomes and career readiness.

Student-Managed Investment Funds (SMIFs) provide a highly practical environment for bridging theoretical concepts with applied investment management. The integration of AI into SMIF courses enables students to simulate real-world portfolio decisions, optimize strategies, and assess risks with greater efficiency. At the same time, traditional tools continue to play a vital role in reinforcing foundational analytical skills and industry norms. Together, they offer a comprehensive and balanced educational experience, preparing students to navigate increasingly data-driven financial workplaces.

That said, this study is not without limitations. The findings rely on self-reported student data, which may be subject to bias, social desirability or overestimation of actual learning gains. Moreover, because the study is based on a single institution—Valparaiso University—its generalizability to other SMIF programs with different structures, resources, or student profiles may be limited. In addition, the absence of a control group or longitudinal assessment makes it difficult to isolate the impact of AI integration from other instructional variables.

Future research should build on these findings through controlled experimental designs that compare cohorts with and without AI exposure to assess differences in measurable learning outcomes such as analytical accuracy, decision quality, and communication effectiveness. Longitudinal studies examining skill retention post-graduation, as well as multi-institutional comparisons across varied SMIF contexts, would provide stronger empirical evidence for curriculum design. These directions not only address current limitations but also hold potential to yield contributions to the teaching and learning in finance scholarship.

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Appendix A

Questionnaire on the Use of AI Tools vs. Traditional Platforms in SMIF

This questionnaire aims to evaluate learning outcomes using AI-driven tools (e.g., FinChat, OpenAI, or others) and traditional platforms (e.g., Bloomberg, Yahoo Finance, or others) in the context of SMIF. Please answer the following questions based on your experience using these tools.

I. Quality of Analysis

1. How effective was AI in helping you analyze individual stock performance?

Very effective | Effective | Neutral | Ineffective | Very ineffective

2. How effective was **traditional tools** in helping you analyze individual stock performance?

Very effective | Effective | Neutral | Ineffective | Very ineffective

3. How would you rate your ability to create well-rounded investment strategies using **AI** tools?

Excellent | Good | Average | Below Average | Poor

4. How would you rate your ability to create well-rounded investment strategies using **traditional tools**?

Excellent | Good | Average | Below Average | Poor

5. To what extent did **AI** help you consider both risk and return when analyzing potential investments?

A great deal | Considerably | Moderately | Slightly | Not at all

6. To what extent did **traditional tools** help you consider both risk and return when analyzing potential investments?

A great deal | Considerably | Moderately | Slightly | Not at all

7. Did **AI** enable you to analyze portfolio diversification (sector and asset class distribution) more efficiently than traditional methods?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

8. Did **traditional tools** enable you to analyze portfolio diversification (sector and asset class distribution) more efficiently than other methods?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

II. Decision-Making Improvements

9. Did **AI** improve your confidence in making investment decisions based on real-time data and AI-driven insights?

A great deal | Considerably | Moderately | Slightly | Not at all

10. Did **traditional tools** improve your confidence in making investment decisions based on real-time data and analysis?

A great deal | Considerably | Moderately | Slightly | Not at all

11. How much time did **AI** save you in making decisions compared to manually gathering and analyzing data?

A lot of time | Some time | Very little time | No time

12. How much time did **traditional tools** save you in making decisions compared to manually gathering and analyzing data?

A lot of time | Some time | Very little time | No time

13. Did **AI's** automation features (e.g., portfolio suggestions, risk assessments) lead to better decision-making outcomes compared to traditional methods?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

14. Did **traditional tools'** analysis features (e.g., data charts, financial reports) lead to better decision-making outcomes compared to other traditional methods?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

15. Did **AI** help you identify optimal entry and exit points in the market more effectively than traditional tools?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

16. Did **traditional tools** help you identify optimal entry and exit points in the market more effectively than other tools you've used?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

III. Clarity of Performance Visualization

17. How helpful was **AI** in generating clear visual representations for portfolio performance?

Very helpful | Helpful | Neutral | Not helpful | Not at all helpful

18. How helpful was **traditional tools** in generating clear visual representations for portfolio performance?

Very helpful | Helpful | Neutral | Not helpful | Not at all helpful

19. Did **AI** allow you to present your analysis to stakeholders (e.g., professors, investors) in a more understandable way compared to other tools?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

20. Did **traditional tools** allow you to present your analysis to stakeholders (e.g., professors, investors) in a more understandable way compared to other tools?

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

21. How easy was it to use **AI's** visual tools to customize your reports or presentations?

Very easy | Easy | Neutral | Difficult | Very difficult

22. How easy was it to use **traditional tools'** visual tools to customize your reports or presentations?

Very easy | Easy | Neutral | Difficult | Very difficult

**Appendix B
Questionnaire Result**

Appendix Table B1: Scores by Question (FIN420 Investment Management & FIN435 Portfolio Practicum)

Question	5	4	3	2	1	Mean
1. How effective was AI in helping you analyze individual stock performance?	18	3	2	0	0	4.70
2. How effective was traditional tools in helping you analyze individual stock performance?	7	8	3	4	1	3.70
3. How would you rate your ability to create well-rounded investment strategies using AI tools?	9	7	2	4	1	3.83
4. How would you rate your ability to create well-rounded investment strategies using traditional tools?	4	8	9	1	2	3.46
5. To what extent did AI help you consider both risk and return when analyzing potential investments?	16	5	1	1	0	4.57
6. To what extent did traditional tools help you consider both risk and return when analyzing potential investments?	5	10	4	3	1	3.65
7. Did AI enable you to analyze portfolio diversification (sector and asset class distribution) more efficiently than traditional methods?	14	6	2	1	0	4.43
8. Did traditional tools enable you to analyze portfolio diversification (sector and asset class distribution) more efficiently than other methods?	3	6	5	7	2	3.04
9. Did AI improve your confidence in making investment decisions based on real-time data and AI-driven insights?	9	12	1	0	1	4.22
10. Did traditional tools improve your confidence in making investment decisions based on real-time data and analysis?	6	10	2	4	1	3.70
11. How much time did AI save you in making decisions compared to manually gathering and analyzing data?	22	0	1	0	0	4.91
12. How much time did traditional tools save you in making decisions compared to manually gathering and analyzing data?	2	2	16	1	2	3.04
13. Did AI's automation features (e.g., portfolio suggestions, risk assessments) lead to better decision-making outcomes compared to traditional methods?	10	6	3	3	1	3.91
14. Did traditional tools' analysis features (e.g., data charts, financial reports) lead to better decision-making outcomes compared to other traditional methods?	4	7	7	4	1	3.39
15. Did AI help you identify optimal entry and exit points in the market more effectively than traditional tools?	7	14	1	1	0	4.17
16. Did traditional tools help you identify optimal entry and exit points in the market more effectively than other tools you have used?	2	8	5	7	1	3.13
17. How helpful was AI in generating clear visual representations for portfolio performance?	14	5	4	0	0	4.43
18. How helpful was traditional tools in generating clear visual representations for portfolio performance?	6	10	4	2	1	3.78
19. Did AI allow you to present your analysis to stakeholders (e.g., professors, investors) in a more understandable way compared to other tools?	19	2	1	1	0	4.70
20. Did traditional tools allow you to present your analysis to stakeholders (e.g., professors, investors) in a more understandable way compared to other tools?	6	7	8	1	1	3.70
21. How easy was it to use AI's visual tools to customize your reports or presentations?	5	13	3	2	0	3.91
22. How easy was it to use traditional tools' visual tools to customize your reports or presentations?	4	6	10	2	1	3.43

Can Metaverse Enhance Immersive Learning in Online Synchronous Introductory Finance?

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Students in online synchronous introductory corporate finance courses often face substantial challenges, including limited spontaneous interaction and reduced engagement. Unlike traditional in-person settings, online environments restrict real-time clarification of complex concepts, which can lead to decreased motivation and weaker academic performance. To address these limitations, this study investigates the effectiveness of Metaverse-enhanced instruction by integrating virtual reality (VR) hardware—specifically Meta Quest 2 head-mounted displays (HMDs)—within a virtual learning environment created on the Spatial platform. This immersive instructional approach enables students to engage with financial concepts in three dimensions, helping replicate the interactivity of a physical classroom. To evaluate its impact, students were divided into a VR group and a control group, both receiving identical lectures on investment criteria and market analysis. The findings show that students in the VR group demonstrated significantly higher levels of conceptual understanding and engagement. Furthermore, student feedback underscored the instructional value of the VR-based Spatial environment, identifying it as a meaningful enhancement to the introductory finance curriculum. These results suggest that immersive technologies, when thoughtfully integrated, can create promising opportunities for experiential learning in online business education.

Keywords: Introductory Corporate Finance, Online Learning, Synchronous Modality, VR, Metaverse

Introduction

Online synchronous learning has become a vital component of modern finance education, offering a dynamic, interactive platform that bridges theoretical knowledge with practical application. Since the COVID-19 pandemic, its popularity has surged, driven by several advantages that enhance the overall learning experience and student outcomes. First, online learning eliminates geographical and logistical barriers, allowing students to access courses from virtually anywhere. This flexibility is especially beneficial for non-traditional learners, working professionals, and individuals with family responsibilities. Dos Santos (2022) highlights that students increasingly value the ability to balance academic pursuits with other life commitments. Second, rapid technological advancement has significantly enhanced online learning. The pandemic accelerated the adoption of digital tools—such as video conferencing platforms and interactive learning systems—that make online education more engaging and effective. These

technologies have not only made it easier to incorporate guest lectures and real-time demonstrations but have also improved student participation and performance (Akpen et al., 2024). Third, online education is often more cost-effective for both students and institutions. Students save on commuting and housing costs, while institutions benefit from scalability without the need for additional physical infrastructure. Various studies have emphasized these financial advantages, making online learning an attractive option for expanding access. Finally, the availability of diverse digital resources enriches the learning process. Online platforms offer recorded lectures, virtual libraries, and interactive tools, allowing students to learn at their own pace, revisit challenging content, and reinforce understanding.

Despite these benefits, significant challenges persist. Synchronous online learning, while enabling real-time communication, often lacks spontaneity and contextual richness of in-person instruction. Students may hesitate to ask questions or struggle to engage in discussions, particularly when dealing with complex material. Maintaining student motivation and active participation in virtual classrooms can also be difficult. Kaddoura and Al Husseiny (2023) and Zhang et al. (2022) underscore the urgency of addressing issues such as reduced context, engagement, and participation in online instruction. Similarly, Dumford and Miller (2018) argue that online environments may limit collaborative learning and student-faculty interaction, thereby hindering meaningful academic discourse.

Recently, the Metaverse has emerged as a promising solution to many of these limitations, particularly in synchronous online instruction (Ali et al., 2025; Morganti & Bartolomei, 2024; Wang & Shin, 2022). According to Salloum et al. (2023), Metaverse technology creates a novel learning environment that blends four key components: Augmented Reality (AR), Virtual Reality (VR), life logging, and the mirror world. These immersive and interactive elements allow students to experience financial concepts in a more tangible and engaging way. For instance, within virtual environments, students can manipulate financial models, participate in real-time simulations, and collaborate with peers in shared virtual spaces. This aligns with experiential learning theories, which posit that activating multiple cognitive processes enhances comprehension and retention.

Motivated by the emergence of new technology, our research explores how integrating the Metaverse into an online synchronous introductory corporate finance course—an essential component of the undergraduate finance curriculum—can enhance student engagement and understanding. By incorporating Virtual Reality (VR) devices to create a Metaverse-based classroom, we investigate whether this immersive environment can improve comprehension of foundational finance concepts and foster greater engagement. Our empirical analysis indicates that VR instruction using the Spatial.io Metaverse platform effectively bridges the gap between traditional face-to-face instruction and standard online formats, offering a compelling alternative to conventional video conferencing.

To that end, we developed VR-based modules using Meta Quest 2 devices within the Spatial.io Metaverse platform, covering core finance topics such as net present value and investment criteria. These modules simulate a virtual classroom where students engage in real-time, immersive learning alongside classmates and instructors. Designed to emulate the collaborative and interactive nature of traditional instruction, we assess whether this approach improves engagement and knowledge retention. Our study compares a control group using traditional online methods with a treatment group utilizing the Metaverse modules using VR devices. The results indicate that students in the Metaverse environment report higher engagement and a clearer grasp of financial concepts. Qualitative feedback supports this finding, suggesting that the immersive, interactive experience makes complex material more accessible and enjoyable.

This study contributes to the growing body of research on the use of emerging technologies in online education—particularly in the field of finance. By demonstrating the potential of VR instruction delivered through Metaverse platforms to improve student outcomes, we offer a scalable and innovative model that institutions can adopt to modernize their finance curricula. Our findings underscore the transformative potential of VR-based immersive learning delivered through Metaverse platforms like Spatial.io in addressing longstanding pedagogical challenges in online education.

The remainder of the paper is structured as follows: Section 2 reviews the theoretical foundations for integrating the Metaverse into education and its relevance to finance instruction. Section 3 outlines our research design, including module development and study methodology. Section 4 presents the results and discussion of findings. Finally, Section 5 concludes with implications for practice and future directions for incorporating Metaverse into finance education.

Literature Review

The shift to online education has posed significant challenges for both educators and students, particularly in disciplines that rely heavily on interactive engagement, such as introductory finance. Akpen et al. (2024) conducted a systematic review of the impact of online learning on student performance and engagement, emphasizing the decline of spontaneous interactions that typically characterize face-to-face instruction. This is especially problematic in finance education, where complex concepts often require immediate clarification and dynamic discussion.

Dos Santos (2022) explored student motivations in post-pandemic online learning environments, finding that the absence of physical presence can substantially reduce motivation—an effect that is particularly pronounced in quantitative fields like finance, where diminished motivation often correlates with lower academic performance. Similarly, Doo et al. (2023), in their systematic review of online learning research during the COVID-19 pandemic, identified sustained student engagement as one of the most persistent challenges in synchronous online education.

In response to these challenges, the Metaverse has emerged as a promising technological intervention. Kaddoura and Al Hussein (2023) examined the growing use of Metaverse applications in education, defining the Metaverse as a persistent, immersive virtual environment that facilitates real-time interaction and collaboration. Their work highlighted both significant opportunities and ethical considerations in its educational deployment. Expanding on this, Ueno et al. (2024) reviewed Metaverse applications in higher education and noted their potential to replicate key benefits of physical classrooms while introducing capabilities not possible in traditional settings. In particular, they emphasized the power of immersive environments to enhance the visualization of abstract concepts—an asset especially relevant to finance education, where topics like market dynamics and investment strategies can benefit from three-dimensional representation. Further supporting this potential, Morganti and Bartolomei (2024) investigated the use of the Metaverse for developing spatial visualization skills, suggesting applications in finance education where visual representation of data and market trends can aid conceptual understanding.

However, successful implementation of Metaverse technologies in education depends on user acceptance and institutional readiness. Park and Kang (2021), using the Technology Acceptance Model (TAM), identified perceived usefulness and ease of use as critical factors influencing early adoption of Metaverse platforms. Building on this, Wang and Shin (2022) integrated the Push-Pull-Mooring (PPM) and TAM frameworks to examine factors shaping students' intentions to use Metaverse-based educational platforms, highlighting perceived value, social influence, and

technological readiness as key determinants. More recently, Ali et al. (2025) used a dual-staged structural equation modeling–artificial neural network approach to explore continuous usage intentions. Their findings stress that initial adoption does not guarantee sustained use, underscoring the need for continuous evaluation and refinement of Metaverse implementations in education.

Beyond finance, the broader potential of immersive learning environments has been documented across disciplines. Zhang et al. (2022) proposed a comprehensive framework for understanding Metaverse use in education, identifying immersion, interactivity, and embodiment as core features that enhance learning experiences. Their work outlined applications relevant to higher education, including virtual field trips, collaborative problem-solving, and simulated professional scenarios. Tlili et al. (2023) situated Metaverse technologies within the context of "Industry 5.0" and "Society 5.0," arguing that immersive learning fosters human-centered technological integration. Their study suggests that Metaverse-based education not only imparts technical knowledge but also nurtures essential soft skills such as communication, collaboration, and creative problem-solving.

Despite the growing interest in Metaverse applications in education, empirical research examining their effectiveness in specific disciplinary contexts—particularly quantitative fields like finance—remains limited. Much of the existing literature focuses on theoretical models, general educational applications, or technology adoption, without directly addressing the pedagogical challenges of teaching complex financial concepts online.

This study aims to fill that gap by empirically investigating the impact of Metaverse-enhanced learning integrated with VR devices on student engagement and understanding in synchronous online introductory finance courses. By comparing outcomes between a VR-enabled experimental group and a traditional online control group, this research offers concrete evidence on the efficacy of Metaverse technologies in mitigating well-documented challenges in online finance education. In doing so, it builds upon existing literature on online learning limitations, leverages established frameworks for Metaverse integration, and extends technology acceptance research to the specific context of finance education. Ultimately, this study contributes valuable insights into both the practical implementation and pedagogical value of immersive learning environments in a discipline that has traditionally struggled with the limitations of online delivery.

Research Frameworks

Research Design

We conducted an experiment with students enrolled in an undergraduate Corporate Finance course, which functions as an introductory course within the finance curriculum, during the Fall 2024 and Spring 2025 semesters. The course was delivered in a synchronous online format, with weekly live sessions held at fixed times via Zoom. A total of 45 students participated in the Fall and 41 in the Spring. To ensure consistency across semesters, the same instructor taught both cohorts using identical instructional materials and teaching methods.

In the Zoom environment, interaction is facilitated through a combination of whole-class discussions, breakout room activities, and student presentations. Each session typically begins with a lecture segment, during which students may ask questions verbally or through the chat function. Following the lecture, students are assigned to breakout rooms for small-group discussions or collaborative problem-solving tasks. These sessions are time-limited and closely monitored, with the instructor rotating between rooms to provide guidance. Student presentations are conducted

either in the main session or within breakout rooms, with peers offering feedback through structured formats.

However, these forms of interaction are largely structured and initiated by the instructor, with limited space for organic or spontaneous exchanges. The Zoom interface inherently restricts informal peer-to-peer conversation, especially during lecture segments where the focus remains on the instructor and chat use is minimal. Additionally, transitions between breakout rooms and the main session create a rigid structure that limits fluid social dynamics. Students have few opportunities to engage in casual, real-time discussions with classmates outside of assigned activities, unlike in physical classrooms where such interactions naturally occur before, during, or after class. These constraints highlight a key limitation of conventional synchronous online learning and serve as the baseline for evaluating whether the VR-based Metaverse environment offers a more interactive and immersive alternative.

These constraints provided the motivation for incorporating a Virtual Reality (VR) environment using the Spatial.io platform, which offers a 3D immersive space designed to replicate the dynamics of physical presence. In the VR classroom, students are represented by avatars and can navigate the virtual environment freely. This spatial freedom allows them to approach peers, form small discussion groups organically, and engage in side conversations—behaviors that more closely resemble the informal social interactions typical of in-person learning. For instance, several students spontaneously gathered around virtual whiteboards before class sessions to discuss concepts from previous lectures or asked questions directly to the instructor by “walking up” to them after class, behaviors rarely observed in the Zoom setting.

Moreover, the persistent visual and spatial presence of avatars encourages ongoing awareness of peer activity and fosters a sense of co-presence. Unlike Zoom’s grid of muted, often camera-off participants, the VR environment simulates physical proximity, making student interactions more intuitive and less dependent on structured prompts. These emergent behaviors suggest that immersive VR settings may better support the kinds of spontaneous interactions and informal learning moments that are often missing in traditional online delivery formats.

To evaluate the effectiveness of Virtual Reality (VR) as a pedagogical tool in finance education, we implemented a controlled experiment during the Fall 2024 semester. For the Module 1 case study (Appendix 1), we randomly selected 20 students to form the experimental (test) group, while the remaining students served as the control group. The instructor delivered key topics—such as stock market index returns, cumulative index performance, and the shapes of the term structure of interest rates—to the experimental group using a VR environment. The same topics were taught to the control group in a traditional online classroom via Zoom. In both groups, the instructor asked each student to solve problems and incorporated case-based group activities to discuss. Students were assigned to breakout rooms of three to five members to discuss open-ended questions about their analysis and findings, and each group was asked to present their findings to the class.

Similarly, for the Module 2 case study (Appendix 2), we again randomly selected 20 students—excluding those who had participated in the VR-based modality in Module 1—to form a new experimental group, while the remaining students served as the control group. This approach ensured that prior exposure to the VR environment did not influence outcomes in the second module. The instructor covered identical content for both groups, focusing on topics such as Net Present Value (NPV), Internal Rate of Return (IRR), and Profitability Index (PI). The delivery methods remained consistent: the experimental group received instruction through the VR environment, providing an immersive and interactive learning experience, while the control group received instruction via Zoom. To examine the performance of each group, all the students solved

problems (Q1 ~ Q4) in Appendix 2. To further promote active learning, both groups participated in structured case-based group activities through open-ended discussions. Students were placed in breakout rooms of three to five members to discuss a series of open-ended questions related to the case material. These sessions were designed to foster critical thinking, collaboration, and peer-to-peer learning. Each group then presented its analysis and conclusions to the full class, encouraging broader engagement and exposure to multiple perspectives.

At the conclusion of Module 2, we administered the Student Engagement Survey, as detailed in Appendix 3, to assess students' feedback on the effectiveness of the VR-based class modality in the Fall 2024. The same experiment and survey procedure were repeated in the Spring 2025 course.

Introductory Finance Course Details

The introductory finance course examined in this study is an undergraduate Corporate Finance course offered at a college located on the East Coast of the United States. As a core requirement for all business majors—including double/triple majors, for example, combining a business major and math; or a business major, computer science, and English—the course is designed to provide students with a strong foundation in key financial principles and decision-making tools. Each section is capped at approximately 45 students to encourage interactive learning and personalized instruction.

The curriculum spans a wide range of essential finance topics, including financial statement analysis, financial ratios, time value of money, valuation of stocks and bonds, capital budgeting, risk and return, cost of capital, and the weighted average cost of capital (WACC). This study focuses specifically on the introductory portion of the course, which emphasizes the interpretation and application of financial statements. Prerequisites for the course include microeconomics, macroeconomics, principles of accounting, applied calculus for finance, and business statistics, ensuring that students enter the course with a foundational understanding of related disciplines.

To evaluate the effectiveness of instruction and student learning outcomes, we begin by analyzing the structural and demographic consistency across different sections of the course, considering variables such as student backgrounds. We then assess student performance on targeted exam or assignment questions specifically designed to measure their comprehension of financial statement concepts. This focused approach enables a more precise evaluation of students' understanding of the core material introduced early in the course.

Metaverse Platform

To develop our Metaverse-based instructional platform, we created an immersive 3D digital environment where students and instructors interact through avatars, replicating the dynamics of a traditional in-person classroom using Virtual Reality (VR) wearable devices. Specifically, the experiment was conducted using the Meta Quest 2 Virtual Reality (VR) head-mounted display (HMD) within a learning space built on the Metaverse platform Spatial(<https://www.spatial.io>)—a 3D immersive social platform that enables creators to design and share interactive experiences across web, mobile, and VR interfaces.

Within this platform, we constructed a virtual classroom featuring 3D-rendered lecture environments. Educational content was presented through virtual screens, and both instructors and students entered the space using personalized 3D avatars. The platform supported access via VR HMDs, personal computers (PCs), and mobile devices. For consistency and to ensure immersive

experience, all participants in the study used the Meta Quest 2 VR HMD, as shown in Figure 1, Appendix 4.

The instructor employed spatial gestures and virtual annotation tools to deliver real-time visual feedback, simulating the experience of a digital whiteboard (see Figures 2–4, Appendix 4). These tools enabled dynamic communication and enhanced instructional clarity within the 3D space. Participants could engage with the instructor and one another through Spatial. Io’s interactive features, including raising virtual hands, using emojis to express emotional responses, and making limited nonverbal gestures via hand tracking—all while fully immersed in VR.

To provide real-world relevance, we created realistic simulation scenarios in which students took on professional roles—such as financial analysts or executives—within a virtual finance committee setting (see Appendices 1 and 2). This approach aimed to contextualize lessons in a business environment. Students presented findings and investment recommendations in a virtual boardroom designed to mirror real-world corporate meeting spaces. They could "sit" at a virtual conference table, raise hands, and engage in discussions. Financial models—including Net Present Value (NPV), Internal Rate of Return (IRR), and cash flow projections—were displayed on interactive virtual screens or dashboards. These elements functioned like a shared screen in Zoom, but in a far more immersive and three-dimensional environment.

Case Studies and Project Modules

Case study project module 1 as in Appendix 1, *Analyzing Economic Fundamentals and Market Performance*, immerses students in the role of a junior analyst at a fictional asset management firm, where they conduct real-world financial analysis using publicly available data from the Federal Reserve Economic Data (FRED) and the U.S. Department of the Treasury. Students compute and interpret monthly S&P 500 index returns, examine return distributions, assess cumulative market performance, and analyze the term structure of interest rates and yield spreads as economic indicators. Through this process, they gain hands-on experience with Excel-based financial modeling, data visualization, and macro-financial interpretation.

Table 1
Case Study 1 - Learning Objectives and Financial Concepts Covered

Concept	Application in Case
Time Series Analysis	Historical stock data, return computation
Risk & Return	Mean, standard deviation, skewness, kurtosis
Distribution Analysis	Histogram interpretation
Cumulative Returns	Understanding of compounding
Yield Curve and Interest Rates	Slope analysis, spread as recession indicator
Macro-Market Linkages	Connecting interest rates to equity performance
Excel & Data Literacy	Real-world financial data manipulation
Visual Communication	Creating and interpreting financial charts

Specifically, as summarized in Table 1, this case study integrates key financial concepts and analytical skills essential for understanding market dynamics. Through Time Series Analysis, students work with historical stock data to compute returns, reinforcing their ability to analyze financial trends. The Risk and Return component deepen their grasp of market volatility by

calculating and interpreting statistical measures such as mean, standard deviation, skewness, and kurtosis. Distribution Analysis involves creating and analyzing histograms, enabling students to visualize return distributions. By examining Cumulative Returns, they develop an understanding of compounding and long-term market growth. The case also explores Yield Curve and Interest Rates, emphasizing slope analysis and the yield spread as indicators of economic cycles and potential recessions. Macro-Market Linkages help students connect interest rate movements to equity market performance, fostering a holistic view of financial interdependence. Practical skills in Excel and Data Literacy are reinforced through hands-on financial data manipulation, while Visual Communication techniques are applied to create and interpret financial charts, equipping students with essential presentation and analytical skills. This comprehensive approach ensures that students gain both theoretical knowledge and practical experience, preparing them for real-world financial analysis. The project is designed to enhance data literacy, critical thinking, and applied understanding of key finance concepts such as risk and return, interest rate dynamics, and their relationship to market behavior.

In addition, the Module 2 case study project provides students with hands-on experience in capital budgeting by evaluating the financial viability of Project Aurora, an AI-powered wearable device product line. Students apply fundamental techniques such as Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period, and Profitability Index (PI) to assess investment decisions. The exercise reinforces key finance concepts, including the time value of money, risk assessment, and decision-making under uncertainty. Additionally, students enhance their data literacy by using Excel for financial modeling and develop critical thinking skills through scenario analysis, such as evaluating the impact of increased risk or higher discount rates. By interpreting financial data and justifying strategic recommendations, students gain practical analytical skills essential for corporate finance and investment decision-making.

We selected the topics of market analysis and capital budgeting for Metaverse-enhanced instruction because they require multidimensional data interpretation, abstract reasoning, and real-time feedback—areas where traditional online platforms often fall short. In the market analysis module (Appendix 1), students analyze historical financial data from the S&P 500 and the yield curve spread using Excel and government databases. These tasks involve interpreting distributions, identifying economic signals, and visually comparing indicators—activities that benefit greatly from immersive 3D environments where charts, yield curves, and return histograms can be spatially explored and manipulated. For example, students can collectively stand around a large 3D histogram or time-series graph and annotate, rotate, or compare data layers together in real time. In the capital budgeting module (Appendix 2), students evaluate a real-world investment scenario using net present value, internal rate of return, and payback period techniques. VR allows these abstract discounting concepts to be visualized spatially—e.g., showing cumulative cash flows as building blocks over time—while also enabling collaborative decision-making in a virtual boardroom environment.

Table 2
Case Study 2 - Learning Objectives and Financial Concepts Covered

Tasks	Learning Objective
Net Present Value (NPV)	Understand the concept of discounting future cash flows and evaluating project profitability.
Internal Rate of Return (IRR)	Determine the discount rate that results in a zero NPV and assess its role in investment decisions.
Payback Period	Analyze how long it takes to recover the initial investment and compare it to the benchmark period.
Profitability Index (PI)	Interpret the ratio of discounted cash flows to the initial investment to assess project value.

Thus, by engaging with real data, simulating analytical tasks, and interacting with peer students in a Metaverse class environment, these cases foster active learning and provide a strong foundation for more advanced studies in finance, particularly when paired with immersive technologies such as Virtual Reality (VR).

Experiment Results

Table 3 exhibits the summary statistics for the student body enrolled in the introductory finance course for Fall 2024 and Spring 2025. A comparison of student demographics and familiarity levels between Fall 2024 and Spring 2025 reveals a slight decline in total enrollment (from 45 to 41 students) accompanied by modest shifts in gender distribution. Female and male representation both decreased marginally, while the number of non-binary students remained constant. Familiarity levels among female students showed a slight decline, particularly in the “extremely” and “slightly familiar” categories, whereas male students exhibited stable levels of familiarity across semesters. Non-binary students maintained consistent familiarity distributions, while students who preferred not to disclose their gender experienced a reduction in both enrollment and higher familiarity levels. Overall, the data suggests a small decrease in students with high familiarity in Spring 2025, indicating structural and demographic consistency across different sections of the course and the potential benefit of reinforcing foundational content at the start of the term.

Table 3
Summary Statistics for All Students Enrolled in the Class

	# of students		Percent of students	
	Fall 2024	Spring 2025	Fall 2024	Spring 2025
Female	20	18	52.6%	47.4%
Extremely familiar	1		100.0%	0.0%
Moderately familiar	6	6	50.0%	50.0%
Not familiar	4	5	44.4%	55.6%
Slightly familiar	8	6	57.1%	42.9%
Very familiar	1	1	50.0%	50.0%
Male	19	18	51.4%	48.6%

Extremely familiar	2	2	50.0%	50.0%
Moderately familiar	5	5	50.0%	50.0%
Not familiar	3	2	60.0%	40.0%
Slightly familiar	5	5	50.0%	50.0%
Very familiar	4	4	50.0%	50.0%
Non-binary / Third gender	3	3	50.0%	50.0%
Extremely familiar	1	1	50.0%	50.0%
Not familiar	1	1	50.0%	50.0%
Slightly familiar	1	1	50.0%	50.0%
Prefer not to say	3	2	60.0%	40.0%
Moderately familiar	2	2	50.0%	50.0%
Very familiar	1		100.0%	0.0%
Total	45	41	52.3%	47.7%

To explore the impact of Virtual Reality (VR) on student learning in finance education, we conducted a study involving students enrolled in online introductory finance courses during Fall 2024 and Spring 2025. Enrollment totaled 45 students in Fall and 41 in Spring, and both courses were taught by the same instructor using identical materials to maintain instructional consistency. The experimental component of the study was implemented during the Fall 2024 and Spring 2025 semester. In the first module (see Appendix 1), students were randomly assigned to either a VR-based experimental group or a traditional control group. Twenty students participated in the VR group, where key finance concepts—such as stock market index performance and the structure of interest rates—were delivered through an immersive VR platform. The control group received the same content via Zoom. Both groups engaged in small-group, case-based discussions and presented their insights to the class, promoting interaction and collaborative learning.

A similar structure was followed for the second module (see Appendix 2), with a new set of 20 students assigned to the experimental group—ensuring no overlap with the first module’s VR participants—to prevent prior exposure from influencing results. This module focused on fundamental valuation tools, including Net Present Value (NPV), Internal Rate of Return (IRR), and Profitability Index (PI). As before, the experimental group received instruction through the VR environment, while the control group continued with conventional Zoom-based delivery. Both groups participated in structured, discussion-based group work, with students placed in breakout rooms to analyze case questions collaboratively. Each group then presented its conclusions to the entire class. This design aimed to foster deeper engagement, critical thinking, and exposure to diverse perspectives, while isolating the effect of VR as a teaching tool.

Table 4
Student Performance on Case Scenarios: Experimental Group vs. Control Group

Case Studies	Experiment Group	Control Group	Mean Diff.	t-statistics
Panel A. Aggregated				
Module 1	79.15 (5.26)	74.81 (5.12)	4.35	3.87***
Module 2	79.81 (4.28)	75.54 (5.98)	4.27	3.75***
Num. of students	40	46		
Panel B. Fall 2024				
Module 1	80.50 (4.91)	74.65 (5.14)	5.85	3.87***
Module 2	80.25 (4.44)	75.63 (6.06)	4.62	2.85***
Num. of students	20	25		
Panel C: Spring 2025				
Module 1	77.81 (5.08)	74.99 (5.52)	2.81	1.69*
Module 2	79.36 (4.19)	75.42 (6.04)	3.94	2.42***
Num. of students	20	21		

Note: Student performance is evaluated based on the average score for each module question, with each question graded on a scale from 0 to 100. These average scores reflect performance on module-specific assessments, which consist of a mix of short written responses and case-based problem-solving tasks, as outlined in Appendix 1 and Appendix 2. Standard deviations are shown in parentheses. *, **, *** denote 10%, 5%, and 1%, respectively.

Table 4 presents student performance on the case scenarios. Performance was assessed based on the average score for each module question, with individual items graded on a 0 to 100 scale. These averages reflect outcomes from module-specific assessments, which included a combination of short written responses and case-based problem-solving tasks, as detailed in Appendices 1 and 2. The results from the comparative analysis between the experimental and control groups indicate that the implementation of the new instructional approach—namely, the Metaverse—had a consistently positive and statistically significant impact on student performance across both modules. As shown in Panel A, when aggregating results across all terms, students in the experimental group outperformed those in the control group by 4.35 percentage points in Module 1 and 4.27 percentage points in Module 2. Both differences are statistically significant at the 1% level, indicating that the intervention led to meaningful improvements in learning outcomes.

A closer examination of semester-level performance provides further insights. In Fall 2024 (Panel B), the experimental group exhibited the largest performance gains, with increases of 5.85 percentage points in Module 1 and 4.62 percentage points in Module 2—both significant at the 1% level. In contrast, during Spring 2025 (Panel C), while the experimental group continued to outperform the control group, the magnitude of the differences was somewhat smaller. The gain in Module 1 was 2.81 percentage points and marginally significant ($p < 0.10$), while the 3.94 percentage point improvement in Module 2 remained statistically significant at the 1% level.

Overall, these findings suggest that the Metaverse-based instructional intervention effectively enhanced student performance, with particularly strong results observed during the Fall 2024 term. Student feedback on the Virtual Reality (VR) learning environment reveals a broadly positive experience characterized by heightened engagement, interactivity, and conceptual understanding. Many students reported feeling more immersed and focused compared to traditional online platforms, with several comments emphasizing the sense of presence, reduced distractions, and enhanced motivation. The immersive nature of the VR platform—described as "highly engaging"

and "very intuitive"—appeared to replicate the feeling of being physically present in a classroom. This led to more dynamic discussions, better focus, and a deeper sense of community. The novelty of the environment was frequently cited, with students appreciating the innovative approach, unique classroom format, and the opportunity to explore new ways of learning.

In addition to the immersive experience, students valued the interactive elements that supported collaboration and conceptual understanding. Features such as collaborative whiteboards, interactive simulations, and 3D visualizations facilitated hands-on learning and problem-solving in shared virtual spaces. The clarity of instructional materials, structured layout, and effective communication tools were also praised, suggesting that the VR environment supported both pedagogical effectiveness and learner autonomy. Overall, the feedback suggests that the VR-based format not only enhanced student engagement and focus but also contributed meaningfully to learning outcomes through its well-integrated technological and instructional design.

Table 5

Survey Results for Students Engagements in the Metaverse Online Learning Environment			
Engagements	Fall 2024	Spring 2025	Aggregated
Behavioral Engagement	3.80	3.78	3.79
Cognitive Engagement	3.85	3.83	3.84
Emotional Engagement	4.33	4.33	4.33

The survey results shown as in Table 5 provide insight into students' perceived engagement in a Metaverse-based online learning environment, assessed across three key dimensions: behavioral, cognitive, and emotional engagement. Scores range from 1 to 5, with 5 indicating the highest level of engagement. Among the three engagement types, emotional engagement scored the highest, with a consistent rating of 4.33 across both Fall 2024 and Spring 2025. This suggests that the Metaverse modality was especially effective in fostering emotional connections, such as feelings of interest, enjoyment, and a sense of presence. The immersive and interactive qualities of the Metaverse likely contributed to students feeling more connected to the learning experience, their peers, and the instructor.

Cognitive engagement was also relatively strong, with an aggregated score of 3.84, indicating that students were intellectually stimulated and invested in the learning process. This implies that the Metaverse environment may have supported deeper learning, critical thinking, and sustained attention through features like interactive simulations and 3D visualizations.

Behavioral engagement, while slightly lower at 3.79, still reflects a positive level of participation, including attending sessions, engaging in discussions, and completing tasks. The small difference between semesters across all dimensions suggests a consistent and stable experience over time, pointing to the effectiveness and reliability of the Metaverse platform in maintaining student engagement across cohorts.

Table 6
Survey Results from Students in the Metaverse Online Learning Environment

Category	Description	Frequency	Relative Frequency
Interactivity and Engagement	Comments about engaging features, simulations, interactive tools	20	26.32%
Immersion and Presence	Comments on feeling present, avatar use, realistic/class-like experience	12	15.79%
Instructional Design	Clear structure, module organization, focused learning, assignments	9	11.84%
Collaboration and Communication	Breakout rooms, teamwork, communication tools, discussions	8	10.53%
Novelty and Innovation	Unique experience, new/different method, novelty of platform	8	10.53%
Visualization Tools	Visualizations, 3D models, spatial representation	7	9.21%
Instructor Presence and Efforts	Instructor interaction, avatar approachability, efforts to engage	4	5.26%
Technical Functionality	Seamless integration, persistent space/classroom, being able to move around	4	5.26%
Reduced Distractions	Comments about fewer distractions compared to other platforms like Zoom	2	2.63%
Assessment and Activities	Gamified quizzes, structured activities, problem-solving	2	2.63%

In addition, we analyzed the open-ended responses to understand how the Metaverse modules helped students stay engaged, as summarized in Table 6. The analysis reveals that interactivity and engagement emerged as the most frequently cited benefits, accounting for over a quarter of all responses (26.32%). Students emphasized the value of active learning through interactive tools, simulations, and gamified elements that promoted deeper participation. One student shared: “I liked that we had to move around and actually click into spaces to access each part of the assignment—it made it feel more like a task I was solving step-by-step, not just a worksheet.” This comment refers to how Module 1 utilized spatial zones within the Metaverse classroom to organize each financial task. Students were required to physically navigate to different “data zones” to

engage with Excel-based analyses of S&P 500 returns, Treasury spreads, and yield curve visualizations—transforming the process into a dynamic, hands-on experience. Many students reported that this design encouraged them to approach the assignments as real-world problem-solving tasks.

Closely following in frequency, immersion and presence were also highly valued (15.79%), with students expressing appreciation for the enhanced sense of “being there,” made possible by avatar-based interactions and the spatial realism of the virtual classroom. One student noted: “Being in the space made me feel more serious about the work—it wasn’t like a regular Zoom where I could just zone out.” The persistent, avatar-based environment was designed to simulate a physical office or research lab, fostering a greater sense of accountability. In Module 2, for instance, students presented their capital budgeting analyses (e.g., NPV, IRR) in a simulated pitch room, standing beside their team’s visual displays—mirroring real-world finance team presentations. These findings underscore the unique affordances of VR platforms in fostering an engaging and immersive educational experience that traditional platforms often lack.

Beyond interactivity and immersion, students also emphasized the importance of sound instructional design (11.84%) and opportunities for collaboration and communication (10.53%). A clear structure, well-organized modules, and meaningful assignments were considered essential for effective learning, while tools that facilitated group discussions and teamwork were seen as critical for building a sense of community. Novelty and innovation (10.53%) were also frequently mentioned, suggesting that the distinctiveness of the VR platform positively influenced learners’ experiences. As one student remarked: “It was different from anything I’ve done in a finance class. I still remember the yield curve we analyzed in the first module—it stuck with me because of how we explored it in the space.” This highlights how novelty enhanced cognitive engagement. In Module 1, students compared Treasury yield curves from 2015 and 2025 using a 3D chart environment, allowing them to “walk through” time-anchored visualizations. Experiencing abstract data in immersive formats appeared to improve recall and encourage curiosity.

While the overall response to the VR-enhanced modules was positive, students also identified several challenges that warrant attention. The most frequently reported issues related to technical difficulties, such as unstable internet connections, lag, or glitches when transitioning between virtual spaces. These interruptions occasionally disrupted the flow of instruction and required additional troubleshooting. A few students also noted a steep learning curve when first using the VR hardware or navigating the Spatial.io platform, which caused initial frustration during the early sessions. Additionally, a subset of participants mentioned experiencing physical discomfort (e.g., eye strain or motion sickness) during extended headset use. Finally, although most students appreciated the interactive features, some felt that moving between virtual zones was time-consuming or disorienting, especially when switching between tasks quickly. These insights highlight important design considerations and underscore the need for onboarding support, user interface streamlining, and session length moderation in future implementations. By incorporating student-reported limitations, we aim to present a more balanced and credible evaluation of the Metaverse learning environment.

Although mentioned less frequently, elements such as visualization tools, instructor presence, and technical functionality were also acknowledged, underscoring the importance of both pedagogical and technical design in shaping user satisfaction. Overall, the data suggest that VR learning environments are most effective when immersive design is integrated with structured pedagogy and robust collaborative tools.

Compared to the more limited interaction typical of Zoom-based synchronous classes, the VR environment more closely replicated the dynamics of an in-person classroom. The 3D-rendered lecture hall allowed students to move freely within the space, approach peers for spontaneous conversations, and engage in informal discussions before and after class—behaviors rarely observed in Zoom’s more structured, instructor-directed format. For example, during a session on capital budgeting, students spontaneously gathered around a virtual model display to discuss key concepts without any prompting from the instructor, reflecting an increased sense of spatial and social presence.

The use of virtual screens and 3D visualization tools added depth and clarity to complex financial concepts. For instance, a 3D model was used to represent a project’s Net Present Value (NPV) as a multi-level structure, with the initial investment and the present value of future cash flows visually stacked to illustrate their relationship. Students were able to navigate the model, annotate specific components, and participate in guided walkthroughs that fostered a spatial understanding of NPV—something difficult to achieve using static PowerPoint slides or standard screen sharing on Zoom.

Furthermore, the platform’s spatial gesture and annotation features supported more dynamic and embodied explanations. Instructors and students used virtual laser pointers and hand gestures to highlight elements within immersive diagrams—for example, tracing projected cash flows along a virtual timeline during an NPV analysis. These interactive actions helped convey complex relationships in a more intuitive and engaging way than verbal descriptions or on-screen highlights alone.

Post-session surveys revealed that many students found it easier to “follow the logic” of financial concepts when they could “see and move around” the ideas in a 3D environment. Collectively, these features contributed to a heightened sense of presence, interactivity, and conceptual engagement—outcomes that were notably less pronounced in the standard Zoom-based delivery of the same content.

Taken together, the survey data highlight the Metaverse’s potential to enhance emotional and cognitive aspects of engagement while maintaining a solid foundation of behavioral involvement.

Limitations

While the results of this study highlight the potential of Virtual Reality (VR) to enhance student engagement and conceptual understanding in synchronous online finance education, several limitations must be acknowledged.

First, the novelty effect of VR technology may have contributed to the increased student engagement observed. For many participants, this was their first exposure to immersive learning environments, and the initial excitement could have temporarily amplified their motivation. Future research should assess whether engagement levels remain elevated over time as the novelty diminishes.

Second, students encountered technical challenges, including headset discomfort, connectivity issues, and difficulties navigating the VR interface. Although these issues were not widespread, they may have negatively affected the learning experience for some participants. These challenges, initially referenced in Appendix 3, are now explicitly discussed to provide a more complete picture of implementation barriers.

Third, the instructor’s prior training and familiarity with the VR platform may have positively influenced the integration and overall effectiveness of the VR modules. Instructors with less

experience may face a steeper learning curve, which could affect delivery quality and student outcomes. This highlights the importance of faculty training and institutional support when adopting emerging educational technologies.

Fourth, the demographic characteristics of the student sample—primarily undergraduate students who self-identified as comfortable with new technologies—may limit the generalizability of the findings. Students with lower digital literacy or less access to advanced technology may respond differently to VR-based instruction.

Fifth, while students were randomly assigned to experimental and control groups, initial familiarity with the Metaverse was not used as a stratification variable. Although post-hoc checks indicated no significant clustering of highly familiar students in either group, the lack of control for this variable introduces a potential internal validity threat. Future studies may benefit from stratified randomization or including familiarity as a covariate in the analysis.

Sixth, although independent t-tests were used to compare outcomes across groups, the study involved multiple modules and comparisons. A more complex design might have warranted the use of ANOVA or multivariate techniques to account for potential interactions or cumulative effects. While we believe the current analysis aligns with the study's focused research questions, we acknowledge that future research with broader scope or more complex designs should consider these statistical approaches.

Finally, this study was conducted within a single introductory finance course at one institution. While the course structure is representative of many undergraduate finance programs, the findings may not generalize to other academic disciplines, levels, or institutional settings. Future research should replicate the study across diverse contexts to validate and extend the current results.

These limitations offer important considerations for educators and researchers and provide a foundation for further inquiry into the effective use of immersive technologies in finance education.

Conclusion

The challenges students face in online synchronous introductory finance courses demand closer examination. Introductory finance is a foundational requirement for all business majors, yet delivering this content effectively in an online synchronous format presents obstacles. Chief among these is the lack of spontaneous interaction. Unlike in-person classes, where students can readily ask questions and engage in real-time discussions, online formats often inhibit these opportunities, making it harder to clarify complex concepts and sustain engagement. The virtual setting can also diminish motivation and attentiveness, especially among students who do not participate regularly, leading to lower academic performance.

To address these issues, this study investigated whether integrating virtual reality (VR) hardware—specifically the Meta Quest 2 head-mounted display (HMD)—within a virtual learning environment built on the Spatial platform could enhance student engagement and learning outcomes. This instructional approach, which we refer to as Metaverse-enhanced instruction, creates immersive and interactive educational spaces where students can explore financial concepts more tangibly.

Within this Spatial-based VR environment, students engaged in simulations that demonstrated connections between key accounting and finance principles. For instance, students could navigate three-dimensional representations of financial statements, helping them visualize and better understand relationships among financial variables. We hypothesized that using this immersive

method to teach foundational topics—such as the time value of money—would improve conceptual understanding. A controlled comparison between students using VR devices and those in a traditional online synchronous setting, with identical content delivery, showed that the VR group reported higher engagement and demonstrated improved comprehension of key financial topics.

Student feedback reinforced these findings, indicating that the VR-enhanced segments of the course were perceived as both valuable and engaging additions to the curriculum. However, several limitations must be acknowledged. First, the increased engagement may partly reflect a novelty effect of using VR technology, which may diminish over time. Second, while technical issues were limited, some students experienced discomfort or connectivity problems that could affect learning. Third, the instructor's familiarity with the Spatial platform and VR tools may have influenced the smooth implementation, suggesting that instructor training is crucial for broader adoption. Fourth, the sample was drawn from a single institution and consisted mainly of tech-comfortable undergraduates, which may limit the generalizability of the findings. Finally, the intervention was applied in a single introductory finance course, and further research is needed to assess its applicability across other business disciplines and educational levels.

Despite these limitations, our findings suggest that Metaverse-enhanced instruction, when implemented through VR HMDs and platforms like Spatial, holds significant promise for improving engagement and conceptual understanding in online finance education. As educational technologies evolve, carefully integrating immersive platforms may become a valuable strategy for enriching virtual business education.

Acknowledgement

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Appendix 1

Module 1: Case Scenario – Analyzing Economic Fundamentals and Market Performance

Suppose you have been retained by HSU Asset Management Company (HSU AMC) as a junior analyst. Your boss, the head analyst, has requested a market analysis and a thorough report on the findings for Henry Baek, the president of HSU AMC. Your boss has instructed you to follow the step-by-step guidelines to complete the task.

Q1. Go to the FRED website and download monthly S&P 500 index prices from April 1, 2015, to February 1, 2025, in Excel (<https://fred.stlouisfed.org/series/SP500#>).

(Note: To change the frequency, click "Edit Graph", then select "Monthly" in the menu labeled "Modify frequency".)

Q2. Calculate the monthly S&P 500 index returns over the sample period, then compute the mean, standard deviation, skewness, and kurtosis.

(Note: You can use "Descriptive Statistics" in the Data Analysis ToolPak or Excel functions.) Explain the significance of these statistics.

Q3. Plot a histogram of the S&P 500 index returns over the sample period. Analyze the distribution and explain its characteristics based on the shape of the histogram.

Q4. Calculate the cumulative S&P 500 index return over the sample period, then plot the cumulative returns. Provide an interpretation of the plot.

Q5. Go to the FRED website (<https://fred.stlouisfed.org/>) and search for "10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity (T10Y3M)" in the search bar. Download the monthly spreads from April 1, 2015, to February 1, 2025.

Q6. Using the downloaded data in Excel, replicate the spread plot from FRED.

Q7. Analyze the replicated spread plot and compare your findings with the analysis in Q4. Discuss any observed relationships or patterns.

Q8. Visit the U.S. Department of the Treasury website (https://home.treasury.gov/resource-center/data-chart-center/interest-rates/TextView?type=daily_treasury_yield_curve&field_tdr_date_value=2025) to find the Daily Treasury Par Yield Curve Rates for April 1, 2015, and January 31, 2025. Report the rates for both dates and plot each of them. Analyze the plots and provide your economic perspective.

Appendix 2

Module 2: Case Scenario – Investing in Project Aurora – A Capital Budgeting Decision

Background

NovaTech Inc. is a tech firm considering an investment in Project Aurora, a new product line of AI-powered wearable devices. The CFO has asked your team to evaluate the project's financial viability using standard capital budgeting techniques.

Project Details

- Initial Investment: \$500,000 (Year 0)
- Project Lifespan: 5 years
- Expected Cash Flows:
 - Year 1: \$110,000
 - Year 2: \$125,000
 - Year 3: \$140,000
 - Year 4: \$155,000
 - Year 5: \$170,000
- Required Rate of Return (Discount Rate): 10%
- Company Benchmark Payback Period: 3.5 years

Tasks

Your team must evaluate Project Aurora using the following criteria:

Q1. Net Present Value (NPV)

What is the present value of all future cash flows minus the initial investment?

Answer:

Q2. Internal Rate of Return (IRR)

What is the rate of return that makes the NPV of the project equal to zero?

Answer:

Q3. Payback Period

How many years will it take to recover the initial investment from the cash inflows?

Answer:

Q4. Profitability Index (PI)

What is the ratio of the present value of future cash flows to the initial investment?

Answer:

Discussion Questions:

Q5. Based on the above calculations, would you recommend accepting or rejecting the project? Why?

Q6. If the project were riskier than average, how might that affect your decision?

Q7. How would your recommendation change if the discount rate were increased to 15%?

Appendix 3 Student Engagement Survey

Name: _____

Term: _____

Instructions: Please respond to the demographic questions by selecting the appropriate option.

Demographic Questions

1. Gender: Male Female Non-binary / Third gender Prefer not to say

2. Major: Finance Accounting Management Economics Engineering
 Math Sciences Computer Science Others

1. How familiar are you with the concept of the Metaverse before this class?
 Not familiar
 Slightly familiar
 Moderately familiar
 Very familiar
 Extremely familiar

Instructions: Please indicate the extent to which you agree or disagree with the following statements based on your experience in the finance course conducted in the Metaverse.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Behavioral Engagement Questions

1. I actively participated in virtual classroom activities.
2. I completed the assignments and exercises related to the module.
3. I stayed focused during the Metaverse sessions.

4. I interacted with classmates or the instructor during the session.
5. I explored the virtual learning space beyond required activities.

Emotional Engagement Questions

1. I enjoyed using the Metaverse to learn finance.
2. I felt motivated to participate in the virtual finance class.
3. I felt a sense of connection with my classmates during the session.
4. I found the immersive experience engaging and stimulating.
5. I would like to take more courses in this format.

Cognitive Engagement Questions

1. I put effort into understanding the financial concepts presented.
2. I applied what I learned in the virtual session to solve problems.
3. I reflected on how the finance concepts connect to real-world applications.
4. I used different strategies (e.g., note-taking, discussions, rewatching content) to help me learn.
5. I found the learning experience intellectually challenging in a positive way.

Open-Ended Feedback

1. What aspects of the Metaverse module helped you stay engaged?
2. What challenges did you face in this virtual learning environment?
3. How can we improve future Metaverse-based finance modules?

Appendix 4 Virtual Environment and Experimental Setup



Figure 1. Meta Quest 2 VR HMD

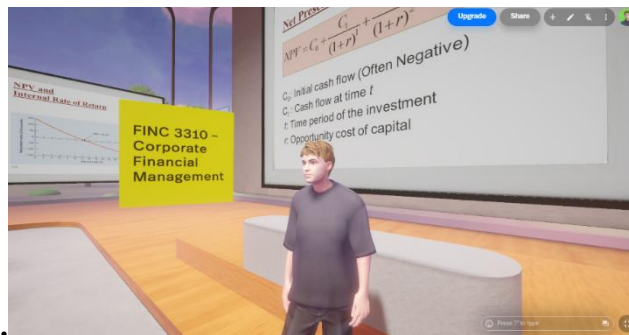


Figure 2. Lecture Scene at Spatial.io



Figure 3. Notes scene in Spatial.io



Figure 4. Emoji expression scene in Spatial.io

Old Line Custom Meat Company

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Old Line Custom Meat Company (OLCM) is the Mid-Atlantic region's largest producer of high quality, dry aged beef, selling to various wholesale and retail customers. The company is run by the founder who has a strong background in finance, the president/operations manager, and the owner's son, a former corporate marketing executive. The company has ten projects to consider, and a capital budget that will only support a few of the projects.

The projects are classified as: product line extensions; new product lines; operational improvements; or safety projects. Ideally the board will select projects to fund from at least three of these classifications.

Students are provided with project descriptions and financial data, including project cash flows, NPV, IRR, and payback calculations and are asked to consider the financial and strategic implications of each project and of groupings of projects. Students will represent the role of one of the leaders of OLCM during a simulated board negotiation to determine how to best spend this year's capital budget.

Key words: capital budgeting; capital rationing; simulation; financial decision making; corporate finance

In December 2021, Old Line Custom Meat Company's (OLCMC) leadership team met to discuss the capital budget for 2022. While COVID had been tough on the company, OLCMC weathered it well and was poised to continue to grow. While all ten projects under consideration had merit, to undertake all of the projects was not feasible given both capital and capacity constraints: there were not enough hours in the day to have the current workforce successfully undertake all of the projects. The total cost of the ten projects was nearly \$1.5 million, and OLCMC proposed sticking to a capital budget of \$300,000, a significant increase to the current asset base of \$5.1 million. The products fell into the following categories, and OLCMC hoped to undertake enough projects to fulfill a minimum of three different categories:

- Product line extension
- New product line
- Operational improvement
- Safety

Company Overview

Old Line Custom Meat Company is a veteran and family-owned and operated custom meat business, offering the finest beef and lamb products in Maryland and the Mid-Atlantic region. Founded in 2011, OLCMC is the merger of Geo. G. Ruppertsberger & Sons, an 1868 legacy, family-owned meat processing company, and Roseda Black Angus Farm (Roseda Farm), a local, veteran and family-owned farm, specializing in beef genetics, founded in 1996.

OLCMC has both wholesale and retail customers and produces both kosher and non-kosher local beef (80%) as well as lamb (20%) products. Sales channels include retail grocery, farm store markets and certain ethnic markets; restaurants and foodservice/dining services; colleges/universities; local sports entertainment venues; and on-demand and online to individual and corporate gifting customers.

Located in Baltimore, Maryland the company has quietly become the largest producer of beef in Maryland and the Mid-Atlantic region, employing approximately 80 full time staff on one shift, Monday – Friday. Products include lamb (lamb loins, chops, and ground lamb), steakburgers, ground beef, all beef hot dogs, loins, steaks, roasts, and beef jerky. OLCMC was a vertically integrated, closed-ended system and able to source verify and trace its products from farm to fork via its genetic breeding process; partnering with a network of 40+ local cow/calf and feeder farms in the area that follow strict dietary and feeding protocols. Harvesting takes place at OLCMC, a wholly-owned, glatt kosher harvest and processing plant in Baltimore. The company incorporates a capital-intensive 14-21 day dry-aging process to ensure the optimum beef product that is of high quality, defined as both consistently tender and juicy.

The company has been growing steadily with a slight dip in profitability due to COVID pandemic related expenses (see Exhibit 1); previous funding had been heavily dependent upon owner financing; in recent years, the firm has begun repaying the owner while utilizing retained earnings and a line of credit to fund growth.

The Beef Industry

In considering growth opportunities, OLCM analyzed several issues including a) the need for additional natural beef in the Mid-Atlantic market; b) the capacity of local firms to supply the volume of beef that would be needed; and c) the feasibility of building an additional processing plant to handle the volume increase if indeed OLCM were to expand beyond its existing capacity. The resulting study identified a strong market for an additional 600 head of natural Angus beef in the Northeast without eroding the company's current 20-30% premium pricing.

Typically, the target consumers for natural and organic food products were shoppers who:

- Were between the ages of 36 and 53
- Had higher levels of education
- Had higher disposable income
- Were not overly price sensitive
- Were active in managing their own health.

Most large retailers carried a commodity type meat line as well as a natural or an organic beef line. Smaller retailers and meat markets might sell only one product offering. Depending upon the retailer's clientele, this may or may not be a natural product. In the retail market segment, the natural or organic beef lines competed against approximately six companies for market share of the natural meat sector.

Typical retail markup was 35% over the distributors' price, with higher premiums paid for product based on the level of claims on the product. Retailers were also willing to pay premium prices for "Prime" and "dry-aged" products.

In response to the market analysis, Ed, Eddie and Bill believed there is adequate demand for additional production and product offerings for OLCM. The trio considered their options.

Resource Allocation

The leadership team at OLCMC prepared the capital budget annually and then discussed it to determine projects to fund. The leadership team consisted of three primary partners, namely the founder, his son, and the president/operations manager who all contribute to the list of projects under consideration; capital budgeting decisions are made by majority rule.

Typically, the firm used both payback period and the internal rate of return (IRR) to evaluate projects. The hurdle rates, established in 1996, based on the type of project were as follows:

Table 1
Hurdle Rates

Project Type	Minimum Acceptable IRR	Maximum Acceptable Payback (in years)
Product line extension	25%	3 years
New product line	30%	2 years
Operational improvement	20%	3 years

There were no criteria for evaluating safety projects.

Hurdle rates were set based upon the perceived risk of each product category, with more risky projects expected to earn a higher internal rate of return (IRR) and to pay back more quickly.

OLCMC re-evaluated its weighted average cost of capital (WACC) annually, and having just concluded this analysis, the leadership team was using 10% as its WACC despite a WACC of 13% for the beef industry.

Project Expenditures

The following projects were up for consideration at the annual capital budget review committee meeting (Table 2):

Project	Expenditure (\$000's)
1. Farm Store Expansion	100
2. Food Truck/Food Grilling	145
3. Website Marketing Expansion	115
4. Meatballs	45
5. Beef Deli Products	60
6. College/University Offering	139
7. Installation of a Second Shift	230
8. Delivery: Direct vs. Distributors	137
9. Plant Expansion	300
10. SQF Certification	75

Product/Product Line Extension

Farm Stores

Given the local movement and growth in farm store sales both at an existing OLCMC farm store and at other farm stores that carry OLCM beef, OLCMC was considering building another farm store location; the margins were very high on product sales, and although there were some start-up costs, the sales tended to grow due to word of mouth marketing. While OLCMC was considering the addition of one farm store, there was potential for future growth through 3-4 more farm stores.

Food Truck/Food Grilling

With the proliferation of Food Trucks, OLCMC was considering a food truck/grilling unit that builds both revenue and its brand as the truck moves from location to location and business to business, grilling beef and serving food. Management believed the investment satisfies the sales and brand return, and there was the potential to add a second food truck/grilling unit if this first business is successful. Employees to staff the food truck would need to be hired and a truck with an outdoor grilling unit purchased.

Website marketing expansion

OLCMC recently re-launched its website, roседа.com, including a more robust marketing and educational approach as well as an e-commerce component. The initial investment was \$50,000 with a modest, monthly incremental spend for social media platforms. OLCMC was in the process of determining the most efficient additional digital and social media marketing advertising spend to maximize sales, which yielded over 50% margins on the recent web site overhaul.

New Product Line

Meatballs

Since the primary product OLCMC sells was steak and premium beef products, what remains after cutting steaks is ground beef and hamburger meat, known as trim. With roughly four times the quantity of trim to premium steaks, selling trim is both a competitive advantage (and challenge), yet necessary to extend its selling period year-round. With more families eating at home, and as sales of premium beef have grown, OLCMC had more beef trimming for sale. The company was considering meatballs, either producing the product itself or supplying it to a co-producer in a co-branded approach or private label. The meatball would be priced as a premium product.

Offer Beef Deli Products

OLCMC had strong relationships with several grocery store chains. One opportunity was to offer brisket/cornd beef to large retail grocers, for sale in the deli cases. This could require working with the existing grocery customers or working directly with deli providers (i.e. Boar's Head).

College/University Offering

OLCMC provided beef to a number of regional colleges and universities but was considering expanding this program. Colleges/universities offer a unique opportunity since the primary

product purchased is burgers (trim), and colleges sell a lot of burgers. While OLCMC sold a good bit of hamburger through grille events in the summer months, colleges will purchase the trim products during the academic year, September – May, complementing current trim sales. Plus universities have a number of events throughout the year (parent and alumni events), and branding the products at the events also provides a marketing opportunity to build brand awareness.

The challenges with college/university customers were there is a longer selling cycle which is typically managed through large concessionaires with large national distributors with national contracts. With the growing trend of locavores, individuals whose diet consists of primarily locally grown food, and student interest in working with local companies with fresh food and farm offerings, there seems to be more expectation for national distributors to partner with local firms for farm to table options.

Strengths and benefits of entering the space is that sales can be very strong in a countercyclical calendar for when trimming/ground beef/equivalents are used; and it reaches a younger demographic that allows marketing and brand recognition for the company and helps streamline production for the company, mitigating potential troughs in usage of these trimmings/equivalents.

Operational Improvement

As OLCMC's business continued to grow in revenue, there was a need to look at expansion of production capacity and other operational efficiencies, including in the following areas:

Installation of a Second Shift

With growth in the business, especially in the retail grocery space, OLCMC was considering an expansion to a second shift. There would be opportunities to streamline first shift production and set up the second shift for more straight-line burger production to make both fresh ground products and frozen burger pallets for the grocery stores and farm store customer. The challenge was hiring more meat cutters and employees for the second shift, which has been mitigated, recently. The second shift could generate an additional \$3 million in revenue simply with retail grocery frozen business, which is not the most margin friendly product; however, it does increase capacity on more margin beneficial products, such as steak and whole loin cuts for wholesale, online, and farm store customers.

Delivery: Direct versus Distributors

OLCMC was considering outsourcing most of its delivery business to one or two distributors. The truck drivers are unionized, and the truck fleet is leased. OLCMC would retain a few direct customers that are high margin customers and strategic relationships but turn over delivery to other customers to a distributor. Distributors typically represent numerous companies whereas direct delivery allows OLCMC to maintain closer connections to customers.

Capital/Slaughter Plant Expansion at the Processing Plant

Expanding the processing plant offers significant operational efficiency for the company, with upside potential in refrigerated and dry-aging space, storage and transportation cost savings. Given OLCMC's current capitalization with owner investment, the company was limited with equity infusion to grow its operations by expanding its harvest/slaughter capacity on its current processing footprint. However, a partnership could provide the capital necessary to expand.

In order to create both additional space and operational efficiencies, there would need to be a significant capital investment, likely \$3 - \$5 million which would not come from the partners; however, these funds could come from either a key retail customer, distributor partner or passive strategic investment partner. The company considers this growth potential, knowing the move will shift the company. It would introduce an additional partner and would move OLCMC away from its current customer base to a model with potentially fewer customers but better-margined customers.

Safety Project

OLCMC was contemplating seeking SQF Certification, Level II. SQF is a Food Safety Management Certification, created and managed by the SQF Institute. It is used to control food safety risks. Once your food safety management system is implemented, the system is audited and certified by a third-party certification body.

The Food Safety Certification requirements provide a rigorous system to manage food safety risks and provide safe products for use by companies in the food industry. Though not required, it is becoming an industry standard and is much desired by some of OLCMC's current customers and may potentially attract additional customers; statistics show that approximately 1 out of 4 certified companies are asking their suppliers to achieve certification.

The system, if implemented, will require the purchase of and use of scanners and thermometers and other appropriate documentation tools, from standard use of property, plant, and equipment and cleanliness/maintenance standards important in maintaining and presenting a high quality and environmentally conscious product to end users and customers. It will require an initial capital outlay and annual outlays. Certification can help OLCMC stay competitive and qualified to work with current and potential future customers.

As the leadership team gathered, it prepared to make decisions that could dramatically alter OLCMC going forward.

Exhibit 1
**Old Line Custom Meat Company
 (OLCMC)**

**Summary Financial Data
 (all values in US dollars,
 thousands)**

Summary Financial Data	2019	2020	2021	2022(projected)
SALES	\$16,864	\$17,940	\$22,518	\$24,200
COST OF SALES	\$10,774	\$11,817	\$14,880	
GROSS PROFIT	\$6,089	\$6,123	\$ 7,639	
GP%	36.10%	34.10%	33.90%	
TOTAL EXPENSES	\$5,549	\$ 6,309	\$ 6,877	
EBITDA	\$521	\$ 814	\$ 762	
NET INCOME	\$106	\$ 420	\$ 414	
Total Assets	\$4,930	\$ 4,138	\$ 5,142	
Shareholders' Equity	\$65	\$ 378	\$ 791	

PROJECT (000's)		Farm Store	Food Truck	College Offering	Website	Second Shift	Meatballs	Direct Delivery	Deli Meat	Plant Expansion	SQF Certification
INVESTMENT											
Property		100	145	139	115	230	45	137	60	300	75
Working Capital				12				50		50	
Year	initial outlay	-100	-145	-151	-115	-230	-45	-187	-60	-350	-75
1		-48	-55	-14	0	42	-15	26	30	-11	-125
2		9	-10	12	90	70	12	28	42	23	-125
3		34	60	48	260	93	24	36	55	40	-125
4		42	94	73		112	49	45	62	74	-125
5			122	96		134		48	71	86	-125
6				112		142		54		132	-125
7						154				312	-125
8						180				564	-125
9						240					-125
10											

Undiscounted Sum	-63	66	176	235	937	25	50	200	870	-1200
Payback (years)	N/A	5.45	4.33	2.10	3.13	3.49	5.26	1.71	6.40	N/A
Maximum payback accepted										
IRR	16.46%	7.34%	17.35%	50.99%	37.11%	11.63%	6.34%	65.03%	20.67%	#NUM!
NPV at industry WACC (13%)	(86.11)	(36.05)	29.95	135.68	349.13	(2.19)	(37.52)	114.12	186.24	(716.46)
NPV at OLCMC WACC (10%)	(81.97)	(18.23)	54.94	154.72	440.94	2.78	(22.15)	129.74	290.73	(794.88)