Gym Attendance at the University of Oregon: An Analysis of Student Behavior and Decision Making

By Hunter Wright

Introduction

The health and fitness industry has seen substantial growth since COVID-19 pandemic restrictions were lifted. According to the 2024 Health and Fitness Association Global Report, key developed markets around the world are seeing record high rates of gym memberships among their adult population. The United States leads with 23.7% of surveyed adults saying they belonged to a gym or health club. On top of this, markets with historically lower participation are seeing record growth as health and fitness enters the forefront of the public consciousness. According to an article by Fortune, young adults are going at an even higher rate, and are responsible for pushing attendance to nearly double its pre-pandemic levels. 38% of survey respondents ages 13-28 (Generation Z) said they were a member at a gym or health club. A majority of undergraduate and graduate college students fall into this age range, and most living close to or on campus find themselves near a college gym. Despite increased gym accessibility, college students have a wide variety of responsibilities and commitments that soak up large amounts of time during the week that make consistent attendance difficult. Consequently, though gym attendance rates are rising worldwide, going remains a privilege to those who can afford to spend time there. This makes college students a natural population to study: young and increasingly health-conscious but facing intense time constraints and competing priorities.

Attending a university is a pivotal point in an individual’s life that introduces new friends, responsibilities, and experiences. For many, it is their first time living independently and making decisions on their own. Naturally, an individual's years at university are a critical habit-formation window where they adopt habits and behaviors that they’ll maintain for the rest of their lives. Regular physical activity is one such behavior with both short and long-term benefits that can drastically improve one’s quality of life. Yet even with access to on-campus gyms and increased awareness of fitness, students often struggle to follow through with fitness plans and maintain consistent exercise regimens.

Every day, students are presented with decisions with ramifications that affect their future. Studying, working, relaxing, and other responsibilities all take time out of everyone’s day. These responsibilities all compete with each other for spots in college students’ extremely limited time on a daily basis. Combine this with a lack of motivation, lack of experience, or any other issue that might make it difficult for a student to go to the gym, and it becomes apparent that many students may fail to follow through with consistent exercise plans, ultimately affecting their long-term health.

According to the University of Oregon's Student Recreation Center (SRC) website, “The Student Recreation Center is consistently busy Monday–Thursday during the term… Friday–Sunday, the Rec has much less traffic.” Most students have busy schedules during the week, and much more time on the weekend, so why does SRC traffic decrease when students have more time to go? In this thesis, I use daily patron entrance data gathered by the SRC to analyze short- and long-term trends in attendance and discuss how students struggle to stick with fitness plans and display behavior consistent with present bias when choosing whether or not to go to the gym.

After regressing gym attendance on variables like day of the week, season, and term, controlling for variables like previous day's attendance and membership type, I find strong, statistically significant drops in attendance in short-term (week by week) time periods. Across longer time periods, most attendance fluctuations are negligible or insignificant. These results reinforce the ideas that students at the University of Oregon struggle to maintain consistent exercise regimens and exhibit behavioral patterns consistent with present bias.

The rest of this thesis is organized into the following sections. Section 2 provides a brief literature review consisting of important papers in behavioral economics and related papers studying gym attendance. Section 3 discusses the standard economic model and present bias. Section 4 describes the SRC and provides insights into the data used for my analysis. Section 5 and 6 describe the methods of the analysis and its results, respectively. Finally, the last section contains a brief conclusion discussing my findings.

Literature Review

The primary literature relating to this thesis is Prospect Theory: An Analysis of Decision under Risk, by Kahneman and Tversky (1979). This paper serves as a critique of expected utility theory by providing evidence that humans do not act completely rationally when presented with decisions that involve risk. While Kahneman and Tversky were focused mainly on monetary decisions under risk, I focus on the scarcity of time as another form of currency, where students risk the development of their human capital based on how they use limited time.

As previously stated, my thesis discusses how student behavior shows evidence of present bias in gym attendance patterns. The concept of present bias was formally introduced in "Doing It Now or Later." by O'Donoghue and Rabin (1999). The authors described "the human tendency to grab immediate rewards and to avoid immediate costs in a way that our 'long-run selves' do not appreciate." They called this tendency *present-biased preferences*, and partially attributed it to impatience. In this thesis, I expand this definition to include time as the currency, and not just the medium. Just like money, time is a scarce resource, especially for college students. They must make decisions on a day-to-day basis on how to spend the next hour. They either invest their next hour in exercise (whose benefits accrue slowly over time), or in another activity that provides more immediate rewards like doing homework or leisure. Treating time as the relevant “currency” translates the authors’ framework from money-over-time to activity choice within a fixed daily time budget, with the same prediction of systematic overweighting of the near-term option.

Butera et al. (2021) studied how immediate social emotions were more powerful motivators than delayed material payoffs. The authors randomly selected households across the

U.S. and informed them that they would be publicly ranked based on their electricity usage. Customers that were told they would be labeled as “top savers” reduced their usage by 6% while customers that were warned they could be shamed for over-consuming reduced their usage by 8%. Interestingly, a price reduction of equal monetary value provided no statistically significant change in behavior. While it’s impossible to observe the social implications of going to the gym in the data, insights could provide evidence for immediate psychological rewards encouraging students to overcome present-biased behavior. Students may skip mid-week workouts because the future health benefits feel remote, but an immediate social prompt like seeing friends going to the gym could shift the reference point and raise same-day attendance just as public ranking altered same-day electricity use.

DellaVigna and Malmendier (2006) found that people who bought monthly memberships tended to go infrequently and indirectly pay more per visit than if they had bought a 10-day pass. Much like I intend to analyze in this thesis, the authors observed how individuals failed to stick to a fitness plan, a mistake that cost them money. While students at the University of Oregon don’t directly pay for access to the Student Recreation Center via a membership, they have “pre-paid” in their tuition and fee payments. Once this becomes a sunk cost, each workout feels free, and students can confidently plan to exercise, but present bias coupled with limited time keeps them from following through.

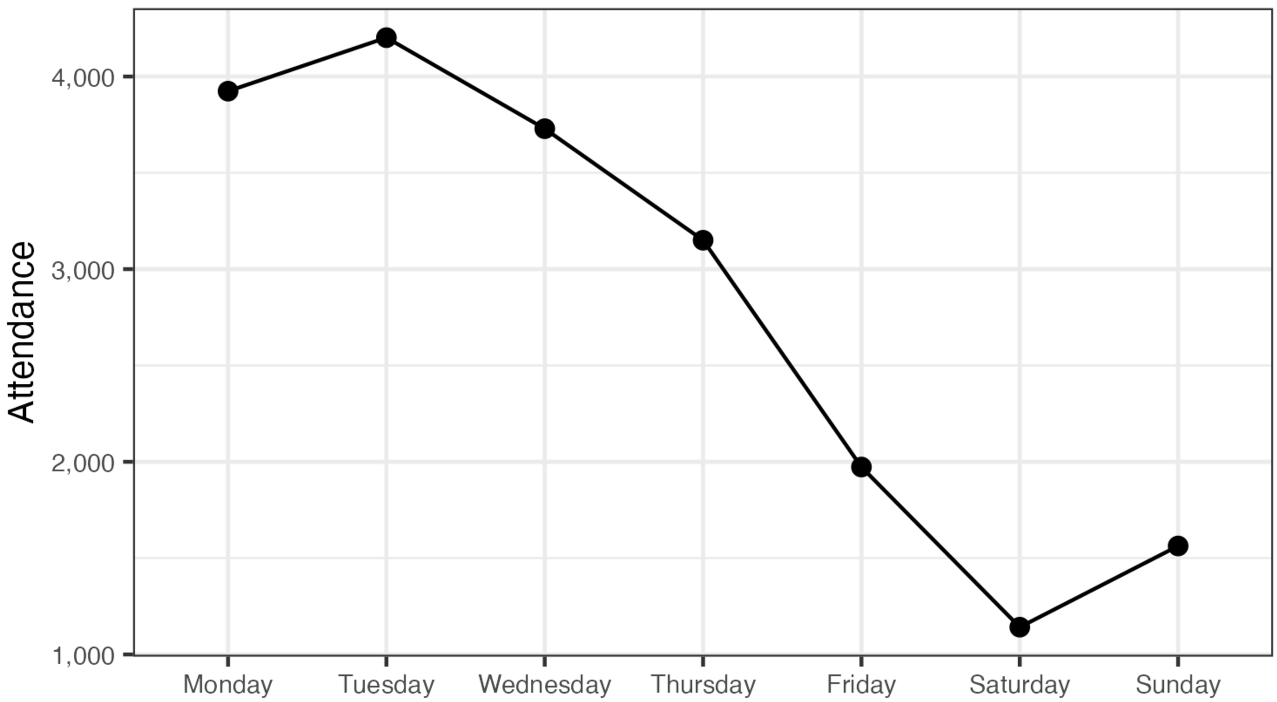
Concepts in Behavioral Economics Theory

Behavioral economics is the study of how people in the real world often deviate from fully rational decision-making. Contrary to what standard economic theory predicts, people don't disregard emotion, habit, and other feelings when making decisions. Behavioral economics primarily focuses on how individuals make decisions with limited resources and this thesis shows that individuals may treat limited time in a similar manner.

The Standard Economic Model

The standard economic model predicts that all individuals are rational agents that maximize their utility subject to a constraint. Because I aim to analyze how students utilize their time, in this thesis, the agent's constraint is the number of hours in a day. If this agent was behaving rationally, they would plan and schedule times to go to the gym every week and stick to that plan throughout the year. If students at the SRC behaved this way, we would expect gym attendance to be consistent across all time periods, with a possible slight uptick on weekends when students have more time to go. However, as Figure 1 shows, this tends not to be the case.

Figure 1: Average SRC Daily Student Attendance, Fall 2024



Present Bias

Individuals experiencing a dilemma with ramifications that unfold over time (known as intertemporal choice) may engage in temporal discounting, where they place disproportionately low value on future rewards, even if they are greater than present rewards. This is known as *present bias*. For example, someone may choose to use their disposable income to buy a good (e.g., a car) rather than deposit the money in a savings account, even though investing will ultimately yield them more utility in the long run. In this thesis, I aim to interpret present bias in how individuals utilize their time. For many people, going to the gym is hard and its payoffs take time to materialize. If someone only has two days a week to relax, they might skip the gym on the weekend and spend their time relaxing, because the immediate gratification of relaxing is worth more to them than the future benefit of a consistent gym routine. This could explain why average student attendance is so much lower on weekends, and is a significant departure from the standard economic model's prediction, which interprets this behavior as irrational. It also contributes to individuals failing to stick to fitness plans, as leisure or homework becomes a more attractive way to spend an hour as the week progresses.

Data

Two data sets were collected and used for this analysis. The first displayed simple daily totals grouped by time of day, while the other displayed these totals grouped by membership type. There is a discrepancy in daily total entrances between the data sets, where the membership data set tends to undercount daily entrances, averaging about 277 fewer entrances a day. The reason for this is unknown, but it can be reasonably assumed that this discrepancy has a negligible effect on attendance trends and behavior patterns. The membership data are the only data used in this analysis, because my analysis focuses exclusively on student behavior. Observations where the SRC is closed for any reason, or that were not a part of an academic quarter (i.e. Thanksgiving Break) are removed from the analysis.

Setting

The University of Oregon is the state of Oregon's flagship public university. As a Division I school offering more than 30 club teams and intramural leagues, fitness is a large part of many students' lives. Whether they're rooting for the Ducks, participating in organized sports, or simply exercising on campus, students at UO are incredibly active. The University of Oregon's Student Recreation Center is the primary facility on campus for students to engage in physical activities like weightlifting, swimming, basketball, and other indoor sports. Students, faculty, staff, and community members alike enjoy more than 36,000 square feet of strength training space, a 12-lane swimming pool, and nearly two dozen courts and gymnasiums, among many other amenities. During normal hours, the SRC is open from 6 a.m. - 11 p.m. on weekdays and 9 a.m. - 9 p.m. on weekends.

Data Collection

Almost every person that enters the SRC must scan their ID through one of the turnstiles. These machines record the time and date of every person who walks through. Table 1 shows the summary statistics for daily entries between January 2015 and December 2024 for days where the SRC is open during a particular academic quarter. This accounts for about 72% of the days in the data, which includes a period between March 18th, 2020 and September 17th, 2020 where the SRC closed due to COVID-19. A day was marked as 'closed' if no students entered the gym on a particular day.

Table 1: Student Attendance Summary Statistics

Mean	Median	SD	Min	Max
2336.793	1986	1598.427	11	6796

Table 2 shows the average daily proportion of membership types. Students make up the vast majority of the SRC's daily entrants. It should be noted that "Off-Term Students" are simply students who are not regarded as full-time students because they are taking less than 12 credits of classes. This number is skewed by the heavy increase in this membership type that occurs every summer when students continue to use the SRC while on summer break.

Table 2: Average Daily Entrances by Member

Membership Type	Average Daily Share
Student	87.9%
Off-Term Student	3.5%
Faculty/Staff	2.4%
Community Member	2.2%
Alumni	2.0%
Nonmember	0.9%
PE Staff	0.6%
Other	0.6%

Methods

To analyze both short and long-run attendance dynamics, I regress daily student attendance on lagged attendance, weekday, week-of-term, month, quarter, post-closure status, and finals/dead-week indicators.

$$\widehat{\text{attendance}}_t = \beta_0 + \beta_1\,\text{attendance}_{t-1} + \sum_{d=1}^{6}\gamma_d\,\text{Day}_{d,t} + \beta_2\,\text{Week}_t + \sum_{q=2}^{4}\theta_q\,\text{Quarter}_{q,t}$$
$$+\ \beta_3\,\text{DayAfterClosed}_t + \beta_4\,\text{DeadWeek}_t + \beta_5\,\text{FinalsWeek}_t + \varepsilon_t$$

The first term in the regression is β_0, the intercept term. This represents the model's expected attendance when all other coefficients are equal to zero. β_1 is the lag term, where t is a subscript for the calendar-day. The coefficient here is a decimal representing what proportion of the previous day's "surprise" or deviation from the expected value is present in today's count. The next term represents day-of-the-week fixed effects: each day's difference in expected attendance relative to Monday. γ_d represents each individual day's coefficient. β_2 describes the change in students as the quarter progresses. The coefficient represents the change in students on a weekly basis. Next, quarter fixed effects describe the average difference in attendance across different academic quarters, or terms. There are four quarters, Summer, Fall, Winter, and Spring. Fall is the baseline quarter that the other three are compared to, with θ_q representing each quarter's coefficient. β_3, β_4, and β_5, are all binary variables describing whether the SRC was closed the previous day, if it's dead week (the week before finals week), or finals week respectively. All are equal to one if the requirement is met, and zero if not.

Because I'm working with time series data, I conducted several tests to ensure unbiased estimates. The daily attendance counts displayed both conditional heteroskedasticity (Breusch–Pagan $\chi^2 = 186.7$, $p < 0.01$) and positive serial correlation (Durbin-Watson = 0.47). To maintain sound standard error measures, I report Newey–West heteroskedasticity and autocorrelation-consistent (HAC) standard errors with a seven-day bandwidth. Additionally, an autocorrelation function (ACF) test revealed strong AR(1) persistence, necessitating the addition of a lagged dependent variable.

Results

Both tables represent two sets of predictors from the same model. The first one reports day-of-the-week fixed effects with and without a one-day lagged variable, representing short term trends in attendance. The second table reports week of the term and quarter fixed effects, , dead-week and finals-week dummies, with and without a one day lagged variable. This represents attendance trends over a longer term, as each quarter of the academic year at the University of Oregon is 11 weeks, or 12 in the summer.

Table 3: Short Term Trends

	Dependent variable:			
	Student Attendance		Log Student Attendance	
	No Lag	With Lag	No Lag	With Lag
	(1)	(2)	(3)	(4)
Intercept	4,098.528***	2,659.550***	8.370***	2.627***
	(117.694)	(121.614)	(0.060)	(0.307)
Tuesday	−16.346	−1,225.812***	−0.012	−0.698***
	(34.674)	(87.921)	(0.014)	(0.040)
Wednesday	−169.231***	−1,454.326***	−0.076***	−0.798***
	(38.202)	(77.579)	(0.017)	(0.037)
Thursday	−450.164***	−1,665.094***	−0.172***	−0.865***
	(36.404)	(74.675)	(0.017)	(0.033)
Friday	−1,314.017***	−2,305.806***	−0.528***	−1.126***
	(49.357)	(80.043)	(0.023)	(0.034)
Saturday	−2,147.805***	−2,532.870***	−1.061***	−1.420***
	(68.341)	(73.523)	(0.022)	(0.024)
Sunday	−2,091.723***	−1,915.755***	−0.966***	−0.909***
	(64.040)	(65.423)	(0.017)	(0.025)
Lagged Student Attendance (t-1)		0.682***		
		(0.035)		
Lagged log-Attendance (t-1)				0.779***
				(0.039)
Observations	2,663	2,662	2,663	2,662
Adjusted R^2	0.717	0.861	0.753	0.916
Note:				*p<0.1; **p<0.05; ***p<0.01

All models show a strong statistically significant decrease in attendance as the week progresses, culminating in more than 2,000 fewer students attending on Saturday than Monday on average. Model 2 incorporates a lag term to account for strong AR(1) persistence, capturing pure day-of-the-week effects. The intercept expects 2,659 students to attend on Monday on average, declining to an intraweek low on Saturday. The lagged attendance variable predicts that about 68% of the previous day's "surprise", if any, carries on to the next day. Controlling for this "habit" raises Adj. R^2 from 0.7 to 0.87, indicating that yesterday's turnout is a strong predictor for today's but isn't able to carry the prediction alone.

Figure 2: Day-of-the-Week Effects

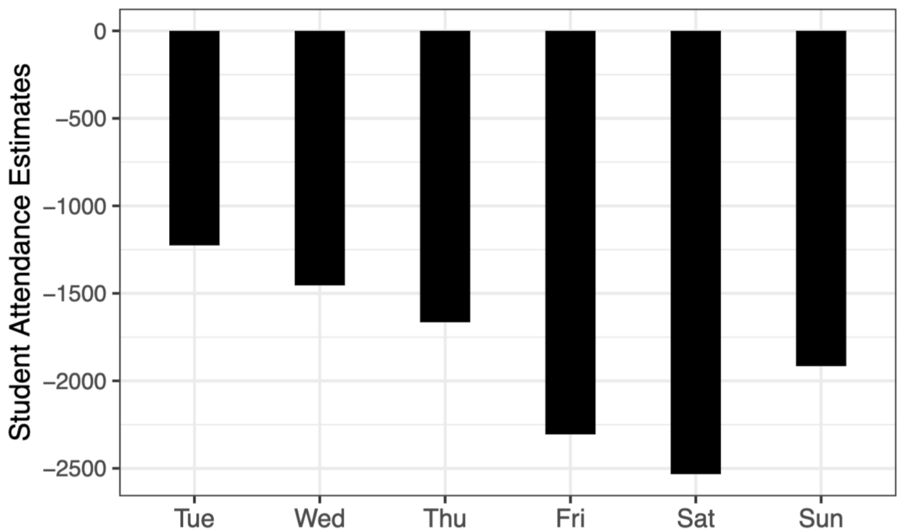


Figure 2 visualizes the weekday coefficients from Model 2. These results both reinforce the idea that students are struggling to stick to weekly fitness plans and mirror weekly averages shown in Figure 1.

Focusing on logged student attendance, similar relative magnitudes in the log model suggest that these findings are not driven by a few high head-count days, but rather consistent patterns in attendance. Incorporating the lag term into the logged model increases the Adj. R^2 to 0.916, even further evidence in strong day-to-day persistence. With a value of 0.806, today's percentage deviation from trend is 0.806 times yesterday's.

Table 4: Long Term Trends

	Dependent variable:			
	Student Attendance		Log Student Attendance	
	No Lag	With Lag	No Lag	With Lag
	(1)	(2)	(3)	(4)
Intercept	4,098.528***	2,659.550***	8.370***	2.627***
	(117.694)	(121.614)	(0.060)	(0.307)
Week of the Term	−76.546***	−34.081***	−0.030***	−0.012***
	(14.382)	(6.033)	(0.009)	(0.003)
Winter	349.244***	117.522***	0.046	0.008
	(125.165)	(44.638)	(0.091)	(0.020)
Spring	66.106	34.317	−0.021	−0.003
	(110.586)	(37.082)	(0.058)	(0.015)
Summer	−2,379.243***	−736.376***	−1.813***	−0.420***
	(77.869)	(98.850)	(0.056)	(0.076)
Week Before Finals	28.817	55.903	0.071	0.034*
	(146.408)	(47.337)	(0.085)	(0.020)
Finals Week	−1,562.323***	−635.702***	−0.709***	−0.300***
	(121.293)	(75.335)	(0.084)	(0.031)
Observations	2,663	2,662	2,663	2,662
Adjusted R^2	0.717	0.861	0.753	0.916
Note:				*p<0.1; **p<0.05; ***p<0.01

Long-term trends show weaker significance and intensity in comparison with day-by-day changes. Controlling for AR(1) persistence, there are sizable coefficients on summer and finals week variables. The coefficient on Week of the Term is statistically significant but not large. At about -34 students, this provides evidence against any major long-term drop in attendance as the quarter progresses. Student attendance varies greatly within each week, but this pattern continues across all weeks of the term at about the same magnitude. In other words, these results undermine the idea that students start strong in week 1 and slowly abandon the gym as the quarter progresses.

Quarter fixed effects coefficients describe how average attendance changes across different periods of the year. With fall as the reference point, winter shows a relatively small increase of 117 students. This similarity in attendance could be attributed to unobserved variables like rainy weather reducing immediate rewards like outdoor activities or lounging outside. Unsurprisingly, summer coefficients show massive drops, coinciding with most students leaving campus. Spring and dead week coefficients show little or no significance, with the finals week estimate reporting -635 students, which correlates with students' schedules being dominated by studying and preparation for finals. The opportunity cost of all hours during finals week is much higher, leading to lower attendance on average.

Conclusion

The original question to be answered in this thesis was, “Why does SRC attendance decrease over the weekend when students have the most time to go?” The answer is that students at the University of Oregon fail to stick to fitness plans and show evidence of present bias when deciding how to spend their limited time each day. As shown in the results section, the reference point (Monday) represented a fresh start every week when the most students would go. However, as responsibilities and other time sinks accumulate over the week, students under-deliver on their fitness plan and chase “immediate rewards” or actions with benefits that unfold much more quickly than the benefits from exercise. These intertemporal decisions resulted in fewer hours spent at the gym on the weekend in favor of time dedicated to leisure or other recreational activities outside of the SRC.

Though the regression in this analysis presented a solid model of student attendance over time, there are several confounders that could affect the results and takeaways of this thesis. Variables like weather, social media, and local events could be responsible for variation unaccounted for. Furthermore, the data does not observe how long a student remains in the SRC or what type of workout they do, if any. Lastly, this thesis does not include any insight into how patterns may have shifted as a result of the COVID-19 pandemic or the rising popularity of fitness on social media in the past five years.

A student’s years in college are incredibly formative and the decisions they make and habits they form last a lifetime. Understanding how psychological biases can affect long term health is paramount in helping young adults set themselves up to lead long and fulfilling lives regardless of how or when they exercise.

Citations

Acland, D., & Levy, M. R. (2015). Naiveté, projection bias, and habit formation in gym attendance. Management Science, 61(1), 146–160.

Bradley, Jordyn. “Is Your Gym Overflowing? A New Study Shows Gym Use Is Nearly Double Pre-Pandemic Levels and Gen Z Is Driving the Trend.” Fortune Well, https://fortune.com/well/article/gym-use-increase-pandemic-gen-z/.

DellaVigna, Stefano and Ulrike Malmendier. (2006). "Paying Not to Go to the Gym." American Economic Review, 96 (3): 694–719.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-291.

O'Donoghue, Ted, and Matthew Rabin. (1999). "Doing It Now or Later." American Economic Review 89 (1): 103–124.

Thaler, Richard. (1985). Mental Accounting and Consumer Choice. Marketing Science, 4(3), 199–214.

Tversky, Amos, & Daniel Kahneman. (1991). Loss Aversion in Riskless Choice: A Reference-Dependent Model. The Quarterly Journal of Economics, 106(4), 1039–1061.

“The 2024 HFA Global Report.” Health & Fitness Association, https://www.healthandfitness.org/publications/the-2024-hfa-global-report/.

https://admissions.uoregon.edu/uo-facts

https://rec.uoregon.edu