



Empirical Evidence: TimelyCare Can Improve Student Retention

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Executive Summary

TimelyCare is higher education's most trusted virtual health and well-being provider, with a mission to foster student success and improve the health and well-being of campus communities. TimelyCare's comprehensive suite of services includes mental health counseling, on-demand emotional support, medical care, psychiatric care, health coaching, success coaching, basic needs assistance, faculty and staff guidance, peer support, and self-guided wellness tools. Founded in 2017, TimelyCare now serves millions of students, educators, and staff at more than 400 campuses nationwide.

Mental health issues are increasingly prevalent among college students, and research highlights mental health as a major factor in predicting students' educational outcomes, including GPA and attrition. A growing body of research from student surveys to empirical studies suggests effective mental health care can combat these effects and support student success.

In the following report, we reveal the results of a first-of-its-kind study that evaluates how a college or university's partnership with TimelyCare can impact student retention. Using rigorous research methods, we compared retention rates for TimelyCare customers against a well-matched group of non-customers. Analyses represent more than one million students from 316 institutions nationwide.

Key Takeaways:

- Findings indicate a positive, significant effect, providing new evidence that TimelyCare's virtual mental health services can increase student retention rates.
- TimelyCare partner schools' retention rates were 1.3 percentage points higher than would be expected if they did not have TimelyCare services.
- These novel findings provide support for the statement that virtual mental health services may increase student retention.
- These results add to a growing body of evidence suggesting that high-quality mental health care, such as that provided by TimelyCare, can support student success.



Introduction

Colleges and universities urgently need help to address students' mental health needs. A recent nationwide study representing more than 350,000 students found that more than 60% met the criteria for one or more mental health problems. **Higher education leaders are rightfully concerned about their students' health and well-being.** Unfortunately, survey data indicates on-campus resources may be unable to meet the growing demand. TimelyCare's virtual services fill gaps in schools' on-campus mental health support.

To ensure this adjunctive support is impactful, **TimelyCare is committed to rigorously evaluating clinical outcomes.** For example, TimelyCare's Measurement-based Care (MBC) initiative results demonstrated clinically significant improvements for patients with severe depression or anxiety. These findings are particularly important in light of limited efficacy evidence among digital mental health interventions tailored to higher education contexts. Research also suggests a virtual platform may reduce barriers to care for students of color. TimelyCare's recent peer-reviewed study - representing more than 500,000 students - revealed a disproportionately high number of Asian, Black, and Multiracial students accessed virtual mental health services. These results are especially striking given observed race/ethnicity inequities in accessing care.

The present report highlights one downstream result of this effective treatment: **improved student retention**. Retention rates reflect the percentage of students who re-enroll at their institution during the subsequent academic year. As might be expected, poor mental health is consistently linked to lower retention. One study estimated that depression is associated with a twofold increase in the likelihood of dropping out. The link between effective treatment and increased retention is also well-documented. In a 2024 in-platform survey, 75% of students said they were more likely to complete their course of study (1,173 of 2,769), and/or remain in classes (910 of 2,769) after receiving TimelyCare treatment.

Empirical studies also offer promising results. One such study found students whose counseling reduced their academic distress were retained or graduated at the same rate one semester following treatment as the general student body. Another study observed that students' diagnosed depression was associated with one half of a letter grade (0.49 points) decrease in GPA, whereas treatment was associated with a protective effect of 0.44 points. A similar study found students participating in counseling were more likely to be retained and to graduate. In sum, although mental health problems are challenging, research suggests effective treatment such as that provided by TimelyCare can help students stay in school.

Can TimelyCare Improve Student Retention?

Approach

To evaluate TimelyCare's impact on retention rates, we analyzed data from the Integrated Postsecondary Education Data System (IPEDS). We used propensity score matching to compare 2022 retention rates (the most recent data available at the time of the study) for schools that had TimelyCare versus similar schools that did not. This analytical approach approximates a randomized controlled trial by allowing us to compare TimelyCare customer schools to an objectively similar group of non-customer schools across the same timeframe on the same outcome measure. **This approach's** validity lies in the matching process, which ensures effects are related to TimelyCare instead of characteristics of the schools themselves.

Considering schools' past retention rates strongly predict their future retention rates, for instance, it is crucial to match groups on past retention rates to make a fair comparison. Importantly, this analytical approach directly answers a recent call for more rigorous evaluations among digital mental health interventions: We use a "quasi-experimental evaluation design with a control group that reasonably represents outcomes that would occur without the intervention."

Schools

Analyses included 158 TimelyCare customers and 158 noncustomers, representing more than one million students nationwide. The customer group consisted of schools that began services before or during January, 2022, meaning they had one or more semesters of services prior to the outcome measure in Fall, 2022. Our matching process comprised two steps: First, we began with a possible control group, the non-customer group, which consisted of all schools within the same National Center for Education Statistics (NCES) comparison groups as the TimelyCare customers (1579 schools).

NCES comparison groups are based on an algorithm that includes institutional level and control, Carnegie classification, and enrollment, among other variables, making them a helpful starting point for institutional benchmarking. Then, we used propensity score matching to carefully select a group of 158 schools to serve as our control group.

TimelyCare Services Available to Group







Statistics

We used R statistical software for analyses, using the R Matchlt package for propensity score matching. We used 1:1 nearest neighbor matching without replacement, with a propensity score estimated via logistic regression. Covariates included key demographic measures linked to 2022 retention rates: institutional level, institutional control, highest degree offered, Carnegie classification, institutional grant aid, federal grant aid, the percentage of undergraduates awarded Pell Grants, past full-time enrollment, and past retention rates.

This analytical approach answers the question: **What would TimelyCare customers' average 2022 retention rate be if they did not have TimelyCare?** To estimate the TimelyCare treatment effect, we fit a linear regression model. The outcome was 2022 retention rates, and predictors included treatment (customer vs. non-customer), covariates, and their interactions. We estimated the average treatment effect for the treated population using the R marginaleffects package comparison function.

Results

First, results indicated that our efforts to create an unbiased control group were successful: **groups were statistically well-matched** on factors that might explain differences in the outcome measure (2022 retention rates). After matching, covariates' absolute standardized mean differences ranged from 0 to 0.13 (mean = 0.03) and covariates' variance ratios ranged from 0.94 to 1.14 (mean = 1.04), indicating groups were well-balanced. In other words, propensity score matching helped identify non-customers that were most demographically similar to customers, enabling a fair comparison across groups.

Next, findings revealed a positive, significant effect: **TimelyCare is estimated to increase customers' average 2022 retention rates 1.3 percentage points higher** (*p* = 0.039). In other words, when comparing TimelyCare customers to a well-matched group of non-customers, customer retention rates were significantly higher. As can be seen below, the magnitude of the estimated effect was large. Without TimelyCare, customers' average 2022 retention rates would nearly equal their average 2020 retention rates – a historic low point during the COVID-19 pandemic.



Conclusion

Prior studies show poor mental health negatively impacts student retention, but a growing body of research suggests effective mental health care can help students stay enrolled. Thus, when evaluating partnerships with digital mental health interventions, stakeholders may reasonably wonder, "Were there improvements in retention?" In the present study, we evaluated how TimelyCare impacted student retention by comparing retention rates for TimelyCare partner schools against retention rates for a group of matched non-partner schools.



1.3 percentage points higher average retention rates at TimelyCare partner schools than those that did not have TimelyCare services

We found that, on average, **TimelyCare partner schools' retention rates were 1.3 percentage points higher** than would be expected if they did not have TimelyCare services. These novel findings provide support for the statement that virtual mental health services may increase student retention. More broadly, these results add to a growing body of evidence suggesting that high-quality mental health care, such as that provided by TimelyCare, can support student success.



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