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Abstract

Mathematics Learning Centers (MLCs) have been widely recognized as effective academic support environments in higher education, with substantial evidence linking student participation to improved academic performance, persistence, and engagement. However, much of the existing research relies on aggregate measures of attendance, such as total visits or hours spent. Thus, this limit understanding of the underlying behavioral patterns that drive these outcomes. This study addresses that gap through a quantitative analysis of student visitation behavior within a university-based MLC.

Drawing on a novel theoretical framework that conceptualizes the MLC as a service-oriented “storefront,” this research integrates perspectives from foot traffic analysis, store layout and flow theory, and service operations management. Using de-identified attendance data comprising over 35,000 student visits across multiple semesters, the study examines patterns of usage across time, course, and physical space within the center. Analyses include descriptive statistics, data visualization, negative binomial regression modeling, clustering techniques, and predictive modeling to identify distinct patterns of student engagement.

Findings reveal that MLC utilization is shaped by both course-level demand and temporal structures, but that traditional measures of participation are misleading when not normalized by enrollment. High-enrollment business math courses produced the largest number of total and unique visitors yet exhibited lower participation rates relative to enrollment when compared to smaller calculus courses. This demonstrates that raw attendance alone inflates perceived engagement and obscures meaningful differences in utilization across course contexts.

Temporal analyses further reveal that demand is highly structured and predictable. Peak visitation occurred between 10:00 a.m. and 2:00 p.m., with pronounced surges in the weeks

leading up to coordinated exams. These surges are not uniform across the center. Course spaces that served business mathematics courses and college algebra courses, such as the yellow and green rooms, experienced sharp pre-exam increases in demand. In contrast, course spaces that served calculus, such as the blue room, maintained relatively stable usage patterns. When measured using occupancy rather than check-in counts, these patterns provided a more accurate representation of real-time service demand, offering a more effective basis for staffing and operational planning. Using these occupancy-based models, the study identified optimized staffing thresholds across rooms and time blocks, demonstrating how staffing resources are aligned with predictable demand cycles.

At the student level, distinct engagement patterns emerged. While early-semester visits are associated with higher likelihood of continued usage within the same semester, students who begin visiting later but engage at high frequency exhibited a strong probability of returning in subsequent semesters. This finding reframed traditional assumptions about early intervention by highlighting that sustained engagement, regardless of when it begins, plays a critical role in long-term participation. In practice, this suggests that initiating student engagement at any point in the semester and supporting continued usage once students enter the system becomes the primary objective of MLC operations.

From an operational perspective, these findings underscore the importance of shifting from descriptive attendance metrics to behaviorally informed, service-oriented analytics. Effective MLC management requires not only attracting students, but strategically supporting patterns of repeated engagement, aligning staffing with predictable demand windows, and designing spaces that respond to course-specific usage patterns. By applying a service-oriented analytical lens, this study provides a more nuanced understanding of how students interact with academic support environments and offers actionable insights for optimizing staffing, space allocation, and service delivery. Ultimately, this work contributes to the research literature by linking detailed behavioral patterns of MLC usage to scalable, data-driven strategies for improving student success in mathematics.

Chapter 1
Introduction

Mathematics proficiency in higher education continues to be a critical issue that academic institutions must address. For many students, the transition to postsecondary mathematics is formidable, particularly as students enter with varying backgrounds. Therefore, as students pursue challenging degrees, their need for mathematical support continues to grow. One way many academic institutions have responded is by establishing Mathematics Learning Centers (MLCs).

MLCs are typically physical campus spaces that provide optional tutoring to supplement formal classroom instruction. Their services encompass a spectrum of support, from one-on-one scheduled tutoring sessions to drop-in assistance and communal review sessions for examinations. Because undergraduate mathematics proficiency remains a significant barrier to STEM degree completion and overall student retention (Adiredja, 2019; Saxe & Braddy, 2015), several studies have investigated the efficacy of MLCs as an intervention strategy. A substantial body of research validates the positive impact of MLCs on student outcomes, providing evidence that consistent engagement correlates with higher grades and increased rates of degree completion (Byrne et al., 2022; Rickard & Mills, 2018). For instance, Moore-Russo et al. (2025) found that students who utilized drop-in services more than ten times a semester exhibited approximately 10% higher rates of persistence and a 0.2-point increase in average GPA compared to those who visited infrequently. Collectively, these findings underscore the merit of utilizing MLCs to bolster academic success.

However, there is a significant gap between the reports of MLC effectiveness and a granular data-driven analysis of student-visit behaviors that mediate these positive effects. While research studies show a broad correlation between center visits and academic performance, they examine total visits or hours spent at the center, often not examining the larger patterns of student engagement, particularly across different student populations. Researchers such as Navarra-Madsen and Ingram (2010) acknowledge that simple aggregation of hours spent masks rich behavioral patterns that may provide more critical evidence of MLC performance. Consequently, there is a gap in the understanding of how the frequency, duration, and timing of student visits contribute to academic success.

This study begins to address this knowledge gap through its analysis of electronic log data from a university MLC. Students recorded their attendance by either swiping their identification cards or manually entering their student ID numbers upon entry. Data for each student were collected for each MLC visit, including information such as the time of their visit, the date, the duration of the session, and the course for which assistance was sought. This granularity allowed a deep analysis of student usage patterns, which helped identify where and how the MLC can support the students who visit. This will allow administrators to make data-driven decisions on ways to enhance the effectiveness of the MLC. Therefore, the aim of this study is to provide granular visitation data to deduce trends that provide critical insight to improve the MLC's efficiency through effective resource allocation, thereby helping promote student mathematical proficiency across this university.

Chapter 2
Literature Review

Research on Mathematics Learning Centers (MLCs) is relatively new, but a growing body of literature has begun to examine their impact. This chapter focuses on four major areas of MLC research. First, we analyze the proven benefits of MLCs. MLCs are supportive resources for students, and we will look at the research that demonstrates this claim. Next, we will look at what happens during a tutoring visit. This is one area of our research that we do not address in the current study. Then we will look at the administrative aspects of MLCs. This focus is crucial since our study primarily focuses on assisting administrators in their decisions regarding MLCs. Finally, we will discuss some limiting aspects. We will show why the existing research is incomplete and why there is a need for this study.

Proven Benefits of Mathematics Learning Centers

Help-Seeking Behaviors and the Role of Tutoring in Academic Outcomes

MLCs primarily offer tutoring as their main service. Therefore, understanding center effectiveness requires an examination of tutoring as a formal help-seeking behavior. Moore-Russo et al. (2025) investigated undergraduate behaviors in mathematics tutoring contexts, finding that the decision to engage with services is influenced by both internal and external factors. Their findings revealed a distinct behavioral split: students with greater academic confidence tended to use tutoring proactively as a study routine, whereas those with weaker preparation often engaged reactively, typically immediately preceding examinations. Ultimately, the study confirmed that regular engagement serves as a primary driver of success. Specifically, students who visited the center more than ten times in a semester achieved GPAs approximately 0.2 points higher and 10% higher persistence rates than infrequent visitors (Moore-Russo et al., 2025). Here, persistence refers to a student's continued engagement in their academic pathways, including successful completion of the current course, progression in subsequent math courses, and continued enrollment toward degree completion.

These findings align with a broader body of literature on the psychology of help-seeking, which is defined as an adaptive learning strategy where students identify a need for assistance and proactively seek social or material resources to overcome academic obstacles (Karabenick & Newman, 2006). Research indicates that academic support services are most effective when they are "normalized," meaning the institution frames support centers as an integral part of the learning process rather than a "remedial tool" or a last resort for struggling students. By fostering consistent engagement early, MLCs can shift student perceptions from a stigmatized view of tutoring as a service associated with failing to a valued, common practice for academic excellence. Thus, the MLC serves not merely as a crisis intervention for upcoming exams, but as a strategic resource for students to deepen their mathematical understanding.

Cross-Institutional Evaluations of Mathematics Learning Centers

One of the most comprehensive assessments of MLCs comes from Matthews et al. (2013), whose systematic literature review evaluated mathematics learning centers across a diverse range of institutions. This research serves as a critical piece of evidence for the benefits of MLCs, showing that they consistently contribute to improved learning outcomes. Particularly, their research showcased this impact for first-year students transitioning from secondary to university education. For many students, university mathematics courses are a major hurdle for degree requirements. The presence of an MLC eases this transition by providing resources that bridge pedagogical gaps. Thus, the authors demonstrated the benefits of MLCs in both immediate academics and long-term degree completion.

Additionally, Matthews et al. (2013) emphasized the diversity of MLC models, noting that success is not tied to a single structure. This diversity in MLC models has also been noted in other research (e.g., Byerley et al., 2020; Infante et al., 2022). MLC success is related to a combination of accessibility, staff training, and institutional support. Matthews and colleagues' research showed that some centers thrive with peer tutoring models, while others thrive with professional staff. However, in any case, there was a common thread of consistent availability of targeted, responsive assistance. Their literature review identifies an MLC as an adaptable intervention, capable of being tailored to institutional contexts while maintaining consistent benefits.

Importance of Tutor-Student Relationships

A central finding across the MLC literature is that effectiveness is not driven solely by instructional technique but by the quality of the relationships that form within tutoring environments. Kahu and Picton (2019) examined how tutor–student relationships shape first-year university students' experiences in mathematics-intensive courses. Their qualitative and survey-based findings showed that students who perceived their tutors as approachable, empathetic, and academically supportive reported lower anxiety, greater confidence in their mathematical abilities, and stronger intentions to persist when encountering difficulty. Rather than being incidental, these relational perceptions were directly associated with how students engaged with learning tasks and whether they continued to seek help when challenged.

Importantly, Kahu and Picton found that relational support influenced students' engagement by shaping how safe they felt expressing confusion and asking questions. Students who described their tutors as supportive were more willing to reveal misunderstandings and to remain engaged even when they struggled. This pattern is consistent with their broader conclusion that affective and relational dimensions of learning mediate the relationship between academic challenge and student engagement.

These relational effects are also connected to students' sense of belonging, which Kahu and Picton identify as a key contributor to persistence in the first year. Students who experienced positive interactions with tutors reported feeling more connected to their academic environment and more confident in their place within it. Within MLCs, where repeated tutor–student interactions are common, these relationships provide opportunities for students to develop both academic and social connections, reinforcing the sense of belonging that has been linked in prior retention research to continued enrollment and persistence.

Kahu and Picton's findings suggest that tutor–student relationships within learning support environments do not simply accompany academic assistance. Rather, they are closely linked to students' emotional engagement, willingness to seek help, and intention to persist in mathematics-intensive courses.

Peer Tutoring as a Reciprocal Learning Model

Peer tutoring is one of the most prominent models used in MLCs and has been examined extensively as a mechanism for supporting both learners and tutors. Ali, Anwer, and Jaffar (2015) investigated the effects of peer tutoring on students in mathematics courses and found that the benefits of tutoring extended beyond those receiving assistance. Their results showed that tutors demonstrated improved content understanding, stronger communication skills, and increased confidence in their mathematical abilities because of teaching others. These outcomes indicate that the act of tutoring reinforces tutors' own learning while simultaneously supporting their peers.

For students receiving tutoring, Ali and colleagues reported improved academic performance and greater engagement with course material. The authors attributed these gains in part to the interactive nature of peer instruction, where explanations are delivered by individuals who have recently mastered the same material. This proximity in academic experience allows tutors to recognize common misconceptions and explain concepts in ways that are accessible to fellow students.

Ali and colleagues also observed that students were more willing to ask questions and acknowledge confusion when working with peer tutors rather than in more formal instructional settings. This increased willingness to seek help reduced barriers to participation and facilitated more frequent engagement with academic support. Within the context of MLCs, these patterns suggest that peer tutoring not only provides instructional assistance but also creates a more approachable and interactive learning environment, supporting sustained student use of tutoring services.

Evidence from Course-Specific Tutoring Programs

Several studies provide direct empirical evidence for the impact of course-specific tutoring centers within MLCs, particularly in high-risk gateway courses such as Calculus I. Byerley, Campbell, and Rikard (2018) evaluated a Calculus Center designed to support students enrolled in introductory calculus and compared outcomes for students who used the center with those who did not. Their analysis showed that students who attended the center achieved higher course grades and were less likely to withdraw or fail the course. Moreover, they found that students who visited more frequently demonstrated larger performance gains than those who attended only occasionally.

Rikard and Mills (2018) extended this line of research by examining the relationship between tutoring attendance and final grades in Calculus I. Using institutional data, they found a positive and statistically significant correlation between the number of tutoring visits and students' final course grades. Importantly, this relationship was observed across the full range of incoming achievement levels, rather than being limited to students who were initially at risk.

Together, these studies show that course-specific tutoring centers are associated with improved academic outcomes in Calculus I. Thus, it might be extrapolated that MLCs which serve multiple courses are likely associated with improved academic outcomes across the different courses. Their findings indicate that structured tutoring supports not only students who are struggling but also those seeking to improve or maintain high levels of performance, reinforcing the role of MLCs as both remedial and enrichment oriented academic support environments.

Controlling for Self-Selection in MLC Research: Evidence from Regression Models

A central challenge in evaluating the effectiveness of MLCs is the issue of self-selection bias. Students who choose to attend tutoring services often differ systematically from those who do not, in motivation, prior preparation, and academic habits. Simple comparisons of outcomes between users and non-users may overestimate or underestimate the true impact of MLC participation. To address this limitation, several studies have employed regression-based methodologies to isolate the relationship between MLC usage and academic performance while controlling for relevant background variables.

One of the earliest and most influential studies in this area is Xu et al. (2001), who examined the impact of tutoring center usage on student performance in College Algebra. Their study utilized a regression framework that controlled key predictors of academic success, including SAT scores, high school GPA, mathematics placement level, and demographic variables. After accounting for these factors, the authors found that students who utilized the tutoring center achieved significantly higher final exam scores than those who did not. In doing so, Xu et al. provide strong evidence that MLC engagement contributes meaningfully to student success rather than simply reflecting pre-existing differences among students.

Subsequent research built upon this approach, reinforcing the relationship between MLC usage and improved academic outcomes across institutional contexts. Berry, Mac an Bhaird, and O'Shea (2015) employed similar statistical techniques to examine student performance in relation to mathematics support center attendance. Their findings indicate that students who engaged with support services demonstrated improved academic outcomes even after controlling for prior performance indicators. Importantly, their work highlights that the benefits of MLC participation are not confined to a single institution or course but are observable across different educational settings.

Quantifying the Impact of MLC Attendance Across Institutional Contexts

While regression-based studies help address concerns related to self-selection bias, an additional line of research has focused on examining the consistency of the relationship between MLC attendance and academic outcomes across different institutional contexts. These studies extend beyond single course or single institution analyses, providing evidence that the benefits of MLC engagement are not isolated, but instead generalize across a variety of educational environments, student populations, and support structures.

Jacob and Ní Fhloinn (2019) investigated student engagement with mathematics support services at a university in Ireland, with a particular focus on how attendance patterns related to academic performance. Their study analyzed institutional data to compare outcomes for students who utilized the support center with those who did not. The authors found that students who engaged with the MLC achieved higher course grades and demonstrated improved rates of course completion. Importantly, their analysis also highlighted variation in how students used the center, with more consistent and sustained engagement associated with stronger academic outcomes. This finding reinforces the idea that the benefits of MLC participation are not simply tied to attendance alone, but to patterns of engagement over time.

Similarly, Rylands and Sherman (2018) examined the impact of mathematics support services within an Australian university context, focusing on both academic outcomes and student retention. Their study found that students who accessed support services were more likely to pass their courses and continue in their programs compared to those who did not utilize available resources. They observed that early engagement with support services was associated with improved outcomes, suggesting that the timing of MLC usage plays a critical role in student success.

Integrating Course-specific and Regression Based Evidence of MLC Effectiveness

While individual studies have examined MLC effectiveness through course-specific analyses and regression-based methodologies, a more comprehensive understanding emerges when these approaches are considered together. Course focused studies provide detailed insight into how tutoring impacts performance within specific academic contexts, while regression-based studies strengthen the validity of these findings by accounting for differences in student preparation and self-selection.

For example, Byerley, Campbell, and Rikard (2018) demonstrated that students who attended a Calculus I support center achieved higher course grades and were less likely to withdraw or fail. Similarly, Rikard and Mills (2018) identified a statistically significant relationship between the number of tutoring visits and final course performance, showing that increased engagement was associated with improved outcomes across a range of student ability levels.

When viewed alongside regression-based studies such as Xu et al. (2001) and Berry, Mac an Bhaird, and O'Shea (2015), these results gain additional significance. While course-specific studies establish clear associations between tutoring and performance, regression analyses demonstrate that these relationships persist even when controlling for prior academic achievement and other confounding variables. This alignment across methodological approaches strengthens the argument that the observed benefits of MLC participation are not simply artifacts of student motivation or prior ability but reflect the impact of the support services themselves.

Meta-Analytic Evidence of Tutoring Effectiveness

Tutoring has also been examined through large-scale quantitative syntheses that extend beyond individual courses or institutions. Cohen, Kulik, and Kulik (1982) conducted a meta-analysis of controlled studies evaluating the effects of tutoring across a wide range of subjects and educational levels. Their analysis showed that students who received tutoring consistently outperformed students in conventional classroom instruction. These results indicate that tutoring is one of the more effective forms of academic intervention measured.

Within this meta-analysis, mathematics was one of the subject areas in which tutoring produced particularly strong effects. Cohen and colleagues attributed these gains to the individualized and interactive nature of tutoring, which allows instruction to be adapted to a student's specific misunderstandings and pace of learning. This is especially relevant in mathematics, where conceptual gaps can interfere with subsequent topics.

Cohen et al. also reported that the effects of tutoring were not limited to test scores and grades. Across studies, tutored students demonstrated higher academic motivation, improved study behaviors, and greater academic self-confidence compared with their non-tutored peers. These findings suggest that tutoring influences both cognitive and affective dimensions of learning, providing a foundation for sustained academic engagement beyond a single course.

Impact of Drop-In Tutoring Models

In addition to peer tutoring, many MLCs rely on drop-in tutoring as a primary mode of academic support. Cooper (2010) evaluated the effectiveness of a drop-in tutoring program by examining student participation patterns and course outcomes. The study found that students who used the drop-in center regularly earned higher course grades than those who did not, indicating a positive association between participation and academic performance.

Cooper's analysis also showed that the frequency and consistency of visits were important predictors of success. Students who attended the drop-in center on a regular basis throughout the semester demonstrated stronger academic outcomes than students who visited infrequently or concentrated around exam periods. This pattern suggests that sustained engagement with tutoring services was more beneficial than occasional or last-minute use.

In addition to grade outcomes, Cooper documented the range of ways students used the drop-in center, including brief visits for specific questions and longer sessions devoted to problem-solving and studying. These varied patterns of use reflected the adaptability of the drop-in model to different academic needs. However, the study emphasized that regardless of how students used the center, regular participation was consistently associated with better academic results. Cooper's findings indicate that drop-in tutoring can be an effective model for supporting student learning within MLCs, particularly when students engage with the service consistently over time.

International Evidence of MLC Impact

The effectiveness of MLCs has also been documented outside of the United States. Bhaird and colleagues (2009) examined the impact of a mathematics support center at the National University of Ireland Maynooth on first-year student performance. Their study compared outcomes for students who used the support center with those who did not and found that center users earned higher grades and were less likely to fail their mathematics courses.

Bhaird and colleagues also reported that the magnitude of these benefits differed across student groups. Students from less advantaged educational backgrounds showed larger gains associated with support center usage than students who entered with stronger academic preparation. These findings indicate that participation in the mathematics support center was associated with reduced achievement gaps between student groups.

By documenting similar patterns of grade improvement and reduced failure rates in an international setting, Bhaird et al. provide evidence that the positive associations between mathematics support centers and student outcomes are not limited to U.S. institutions. Their results suggest that structured, supplemental mathematics support can contribute to improved academic performance across different higher education systems.

Synthesis of Proven Benefits

Across the literature, consistent relationships emerge between participation in MLCs and indicators of student success. Course-based studies such as Byerley et al. (2018) and Rikard and Mills (2018) show that MLC usage is associated with higher course grades and lower failure and withdrawal rates in Calculus I. Meta-analytic evidence from Cohen et al. (1982) further demonstrates that tutoring produces statistically significant gains in academic performance across subjects, including mathematics. Together, these findings establish a strong empirical link between engagement with tutoring services and improved academic outcomes.

In addition to achievement, several studies document affective and behavioral outcomes associated with tutoring participation. Kahu and Picton (2019) found that students who experienced supportive tutor relationships reported greater confidence, reduced anxiety, and stronger intentions to persist. Cohen et al. (1982) similarly reported higher motivation and self-confidence among tutored students. These findings indicate that tutoring influences not only what students learn, but how they engage with learning and perceive themselves academically.

The literature also shows that MLCs serve a broad range of students. Rikard and Mills (2018) found that tutoring was associated with grade improvements across different levels of prior achievement, and Bhaird et al. (2009) showed that students from less advantaged educational backgrounds experienced particularly strong benefits from participation in a mathematics support center. These results indicate that MLCs function both as support for students at risk of failure and as a resource for students seeking to strengthen or extend their learning.

At the same time, much of the existing research relies on aggregate measures of tutoring use, such as total visits or cumulative hours (Byerley et al., 2018; Rikard & Mills, 2018; Cooper, 2010). While these measures demonstrate statistically significant associations between usage and outcomes, they do not capture how students distribute or sequence their engagement over time. As Navarra-Madsen and Ingram note, two students with identical total hours may differ substantially in how they use tutoring services, with potentially different implications for learning and persistence. Consequently, although the literature establishes that MLC participation is associated with positive academic and affective outcomes, it also highlights the need for more fine-grained analyses of student engagement patterns within MLCs.

Administrative Perspectives on Mathematics Learning Centers

While the proven benefits of MLCs for students are well established, their success depends heavily on administrative structures, organizational practices, and departmental support that sustain them. The literature on the administrative side of MLCs highlights how institutional priorities, staffing models, funding, and departmental collaboration influence the availability of services and their effectiveness as well as sustainability. A growing body of research has examined these factors, offering insights into how institutions can design and manage MLCs to maximize their impact.

Departmental Change and the Role of MLCs

Cronin, Moore-Russo, Bjorkman, and Mills (2025) view MLCs within a broader framework of departmental change in undergraduate mathematics. Through their synthesis of departmental reform efforts, they argue that MLCs function not as auxiliary services but as "central infrastructure for student success" within departments seeking to improve retention and learning in STEM pathways. Rather than operating independently of classroom instruction, MLCs are most effective when they are deliberately aligned with curricular goals and teaching practices.

Cronin and colleagues emphasize that departments that intentionally coordinate tutoring with course content, assessment practices, and instructional priorities are better positioned to improve student outcomes. As they note, "MLCs are most powerful when they are embedded in a coherent departmental vision of teaching and learning rather than treated as add-on support units" (Cronin et al., 2025). In this way, MLCs reinforce and extend what occurs in the classroom, rather than functioning as a parallel or compensatory system.

The authors also document a persistent tension between grassroots innovation and long-term institutionalization. Many MLCs originate as faculty-driven initiatives responding to local instructional needs, but Cronin et al. observe that "initial efforts to change individual instructor's teaching methods do not often lead to widespread or long-lasting change" (p. 4). To achieve sustained impact, departments must formally recognize MLCs through stable funding, staffing, and inclusion in departmental planning and governance structures.

Without this institutional support, MLCs risk being perceived as temporary, limiting their ability to shape student success in meaningful and lasting ways. Building on this, Cronin et al. (2025) emphasize that lasting change depends on embedding instructional support within broader departmental systems rather than relying on isolated efforts. Their analysis positions MLCs not merely as tutoring sites but as organizational mechanisms through which departments enact reforms in learning undergraduate mathematics.

MLCs as Institutional Frameworks for Support

Menz and Jungic (2015) conceptualize MLCs as institutional support frameworks embedded within broader systems of academic assistance. Rather than viewing MLCs solely as locations for tutoring, they argue that these centers function as visible indicators of an institution's commitment to supporting student success in mathematics. By allocating physical space, staffing, and administrative resources to mathematics support, institutions make the availability of help both visible and legitimate.

Menz and Jungic emphasize that this institutional visibility plays an important role in shaping student behavior. They note that when support centers are centrally located, well-resourced, and formally recognized, students are more likely to view help-seeking as an expected part of academic life rather than as a sign of failure. In this way, the design and positioning of MLCs contribute to patterns of student engagement with academic support services.

The authors also highlight the administrative and logistical challenges associated with operating MLCs at scale. As enrollments in mathematics and other STEM courses increase, institutions must address issues related to staffing, tutor training, scheduling, and space limitations. Menz and Jungic argue that without deliberate planning, these constraints can limit the effectiveness and reach of a learning center. Their analysis therefore frames MLCs not only as instructional spaces but also as organizational structures that require careful integration into institutional systems.

Towards Research-Based Organizational Structures

Building on these institutional themes, Byerley and colleagues (2024) examined how research-based organizational structures support effective administration of mathematics tutoring centers. Their work argued that MLCs were most effective when administrative decisions were guided by systematically collected data rather than by informal impressions or anecdotal experience. Specifically, they emphasized the use of data on student usage patterns, learning outcomes, and student satisfaction to inform decisions about staffing levels, hours of operation, and the types of services offered.

Byerley and colleagues also showed that data-driven administration allowed MLCs to respond more effectively to changes in student demand. For example, when usage data indicated that certain courses or time periods generated higher or lower demand for tutoring, administrators could adjust staffing and scheduling accordingly. This alignment between resource allocation and documented student needs improved both efficiency and service quality.

In addition, Byerley et al. emphasized that research-based administrative practices supported institutional accountability. By demonstrating the impact of tutoring services through data, MLCs were better positioned to communicate their value to department chairs, deans, and other institutional decision-makers. In the context of ongoing budget constraints, their work highlighted that the ability to document effectiveness was an important factor in sustaining and expanding MLC operations.

This perspective is further supported by Infante et al. (2022), who examined variations in MLC structures and practices across institutions, focusing on how differences in organization, staffing models, and service delivery shape student experiences. Their findings indicate that tutoring interactions are not solely determined by individual tutor behavior but are influenced by the broader structural and institutional context of the MLC.

Performance Assessment and Accountability

The theme of accountability is further developed by Johns and colleagues (2023), who examined performance assessment practices for mathematics tutoring centers. Their work addressed the challenge of evaluating MLC effectiveness in ways that extend beyond anecdotal success stories or raw attendance numbers. Johns et al. argued that meaningful assessment required the use of both quantitative and qualitative measures, including student grades, retention rates, student satisfaction surveys, and evaluations of tutor performance.

The authors cautioned that reliance on any single metric could produce misleading conclusions. For example, Johns et al. noted that a center with high attendance, but weak learning outcomes would not be meeting its educational mission, whereas a smaller center with relatively low attendance but strong academic results could be considered highly effective. For this reason, they advocated for multidimensional assessment frameworks that simultaneously captured patterns of usage and indicators of learning.

According to Johns and colleagues, such assessment systems served two critical purposes. First, they provided MLC administrators with data to guide continuous improvement in programming and staffing. Second, they generated evidence that could be used to demonstrate the educational value of tutoring centers to institutional stakeholders, strengthening the case for sustained support and funding.

Tutor Training and Professional Development

Another central component of MLC administration is the preparation and training of tutors. Wepner (1985) examined peer tutor training in the context of mathematics remediation and found that the effectiveness of tutoring was closely related to the quality of tutor preparation. Although peer tutors often entered their roles with strong content knowledge, Wepner reported that they did not necessarily possess the instructional or communication skills required for effective tutoring. Without training, this gap could lead to inconsistent tutoring experiences for students.

Wepner showed that structured training programs improved tutoring quality by focusing on communication strategies, questioning techniques, and ways of responding to student difficulties. Tutors who participated in training were better able to diagnose student misunderstandings and to adapt their explanations in ways that supported learning. These findings indicate that tutor effectiveness was not solely a function of mathematical expertise, but also of pedagogical preparation.

Wepner also emphasized that tutor development was not a one-time process. Ongoing feedback, supervision, and opportunities for reflection were identified as important components of effective tutoring programs. Within MLCs, these findings suggest that administrators play a key role not only in hiring capable tutors but also in providing sustained professional development structures that support high-quality tutoring over time.

Recruitment and Retention of Students

Even the most well-structured MLCs can only achieve their intended outcomes if students actively use the services. Halcrow and Iiams (2011) examined factors influencing student attendance at mathematics tutoring centers, demonstrating that availability of services is insufficient to ensure engagement. Students must be aware of the resources, perceive them as accessible, and believe that participation will contribute to their academic success.

Halcrow and Iiams further emphasized that marketing and outreach are essential administrative responsibilities for MLCs. Centers that actively promote services through classroom visits, faculty endorsements, and peer recommendations experience higher usage rates. Embedding MLC participation into course structures can also increase engagement; examples include offering extra credit for attendance, facilitating exam review sessions, or having instructors present during critical assessments. These strategies illustrate that MLC effectiveness depends not only on service quality but also on intentional efforts to make students aware of, and motivated to utilize, available support.

Synthesis of Administrative Themes

The literature converges on several consistent findings about the conditions under which MLCs operate effectively. Cronin et al. (2025) and Menz and Jungic (2015) both showed that MLCs function most successfully when they are embedded within departmental and institutional structures rather than operating as isolated or informal initiatives. Their analyses emphasized that formal recognition, stable funding, and alignment with curricular goals are central to the long-term sustainability of learning centers.

Across multiple studies, data-driven decision making also emerged as a core administrative principle. Byerley et al. (2024) and Johns et al. (2023) demonstrated that the systematic use of data on student usage, learning outcomes, and satisfaction supported more effective staffing, scheduling, and service design, while also providing accountability to institutional stakeholders. These studies showed that evidence-based administration allowed MLCs to respond to changing student needs and to justify their continued support.

The preparation and ongoing development of tutors was another area of strong agreement in the literature. Wepner (1985) found that tutor effectiveness was closely tied to training in communication, questioning, and instructional strategies, and that ongoing feedback and supervision contributed to higher-quality tutoring. These findings indicate that tutor preparation is a central administrative responsibility rather than a peripheral concern.

Finally, Menz and Jungic (2015) emphasized that the visibility and accessibility of MLCs influenced student participation, suggesting that outreach and institutional positioning played a role in whether students used available support. This body of research shows that the effectiveness of MLCs depends not only on individual tutoring interactions, but also on the organizational, administrative, and institutional structures that support those interactions.

What Happens During the Visit

While much of the literature on MLCs focuses on outcomes or administrative structures, an equally important line of inquiry examines the dynamics of tutoring interactions. Understanding what happens during student visits provides valuable insight into the strategies by which MLCs show their effects. This literature highlights the phases of consultation, the development of tutor expertise, student experiences and perceptions, and the factors that shape attendance and engagement.

Phases of Tutoring Consultations

Schürmann and colleagues (2022) conducted a detailed analysis of tutoring consultations in mathematics learning centers and identified recurring phases within tutoring interactions. Their study described three primary stages: an initial phase focused on identifying the student's problem and goals, a collaborative problem-solving phase, and a concluding phase devoted to reflection and consolidation of learning.

In the initial phase, Schürmann et al. found that tutors worked to clarify the student's concerns and establish a shared understanding of what the student wanted to accomplish. Students often arrived with broadly stated or ambiguous questions, and tutors used targeted questioning to uncover specific misunderstandings or gaps in knowledge. This diagnostic work shaped the direction of the remainder of the session.

The problem-solving phase involved tutors and students working together on mathematical tasks. Schürmann et al. observed that tutors typically used guided practice, offering prompts, hints, and explanations while encouraging students to carry out the mathematical reasoning themselves. This balance allowed tutors to support progress without taking over the problem-solving process.

In the closing phase, tutors prompted students to reflect on what they had learned and how the strategies used in the session could be applied to future problems. Schürmann et al. reported that this reflective component helped consolidate understanding and clarify next steps for independent study.

Overall, their framework characterizes tutoring as an interactive and structured process rather than a one-way transmission of information. By documenting how tutors guide students through diagnosis, problem-solving, and reflection, Schürmann et al. provide a process-based explanation for how tutoring sessions support learning within MLCs.

Tutor Development and Professional Identity

The experience of serving as a tutor has itself been examined as a developmental process. Grove and Croft (2019) studied postgraduate tutors working in a mathematics support center and documented how tutors' approaches to tutoring evolved over time. They found that many tutors initially framed their role primarily in terms of content expertise, focusing on explaining procedures and providing correct solutions. As tutors gained experience, however, their approach shifted toward facilitating student thinking through questioning, dialogue, and shared problem-solving.

A growing body of work within the RUME community has examined tutoring in MLCs as a complex practice shaped by identity, knowledge, decision-making, and instructional beliefs. Rather than viewing tutoring as the transmission of mathematical content, these studies demonstrate effective tutoring depends on how tutors interpret their roles, respond to student thinking, and navigate instructional situations.

For example, Bjorkman and Nickerson (2019) investigated the social organization of MLCs by analyzing how undergraduate tutors position themselves within distinct social groups in the center. Their study aimed to understand how tutors' identities are constructed through participation in the MLC environment. They found that tutors do not operate as a single, uniform group, but instead form subgroups with differing norms, expectations, and approaches to tutoring. These distinctions influenced how tutors interacted with students, including the level of authority they assumed, how they framed mathematical explanations, and how they responded to student difficulties.

Complementing this perspective, Burks, and James (2019) examined the types of knowledge required for effective mathematics tutoring, introducing the concept of Mathematical Knowledge for Tutoring. Their study focused on how tutors interpret and respond to student thinking during tutoring sessions. They found that effective tutors must go beyond procedural fluency, demonstrating the ability to recognize misconceptions, ask productive questions, and adapt explanations based on student understanding. This highlights that tutoring requires a specialized form of knowledge that is distinct from simply knowing how to solve problems.

Extending this line of inquiry, Ryals, Johns, and Mills (2019) explored the challenges tutors face in enacting this knowledge in practice. Their study investigated the concept of "knowing-to act," referring to the ability to make appropriate instructional decisions in real-time. They found that even when tutors possess strong mathematical understanding, they often struggle to determine how to respond in the moment, particularly in complex or unfamiliar situations. This gap between knowledge and action underscores the dynamic and context dependent nature of tutoring.

Additionally, Pilgrim, Miller, Hill-Lindsay, and Segal (2020) examined the beliefs and instructional practices of both graduate and undergraduate tutors in MLCs. Their study aimed to understand how tutors' beliefs about mathematics and learning influence their tutoring approaches. They found that tutors' practices were closely aligned with their beliefs, with some emphasizing procedural guidance while others focused on conceptual understanding and student reasoning. These differences shaped the structure of tutoring sessions and the types of support students received.

Grove and Croft described this progression as a movement from seeing oneself as a "problem solver" toward adopting a more reflective, pedagogical identity. Tutors became more attentive to how students reasoned, where misunderstandings arose, and how to guide students without taking control of the work. This developmental trajectory was shaped by experience in tutoring sessions, reflection on those experiences, and interaction with other tutors and supervisors.

These findings align with earlier work on tutor preparation and training, such as Wepner's (1985) study of peer tutor development, which showed that effective tutoring depended not only on content knowledge but also on the acquisition of communication and instructional skills. Together, these studies indicate that tutor effectiveness develops over time through practice, feedback, and reflection.

Within MLCs, this growth in tutor expertise contributes to the quality of tutoring interactions and to the broader learning environment. As tutors become more skilled in facilitating student thinking, they are better able to support productive and supportive tutoring sessions, reinforcing the role of the MLC as a space for collaborative learning.

Student Experiences in the MLC

Student perspectives provide an important lens for understanding what occurs during visits to MLCs. Duranczyk and colleagues (2006) examined student experiences with learning center services and found that students valued these centers not only for academic assistance but also for the interpersonal and environmental support they provided. Many students described the MLC as a place where they felt comfortable asking questions and acknowledging confusion, particularly in comparison to more formal classroom settings.

Duranczyk and colleagues also reported that students perceived the learning center as a community-oriented space in which they could interact with peers and tutors in supportive ways. These social and emotional dimensions were an important part of how students evaluated their experiences with tutoring services.

At the same time, the authors documented variation in student experiences. While many students reported positive interactions and academic benefits, others expressed frustration when tutors were unavailable, when sessions felt rushed, or when the assistance they received did not align with their expectations. These findings indicate that the quality and consistency of tutoring interactions influenced how students perceived and used MLC services. Duranczyk et al.'s results show that student experiences of MLCs are shaped not only by whether help is available, but by how that help is delivered and how well it meets students' needs during tutoring interactions.

Factors Influencing Perceptions and Attendance

Tinsley and colleagues (2018) investigated the factors that shaped student perceptions of Mathematics Learning Centers and their patterns of attendance. Their study identified convenience, tutor approachability, and perceived relevance of support as primary determinants of whether students chose to engage with the center. For instance, students were more likely to attend centers that were physically close to classrooms or residence halls, highlighting the importance of accessibility in encouraging participation.

Tutor demeanor was also a significant factor in shaping engagement. Tinsley and colleagues found that students who experienced tutors as approachable, supportive, and nonjudgmental were more likely to return for subsequent visits, whereas negative interactions or unhelpful guidance reduced the likelihood of continued attendance.

Finally, the perceived alignment between tutoring and immediate academic goals influenced participation. Students reported greater motivation to engage when they believed that tutoring would help them meet specific objectives, such as preparing for an exam or completing an assignment. These findings indicate that both logistical accessibility and emotional support contribute to sustained student engagement in MLCs.

Revisiting Help-Seeking Behaviors

Christiansen, Coxsey, and Moore-Russo (2022) examined how students' broader help-seeking behaviors influenced the effectiveness of MLC visits. Their study found that students who integrated tutoring into their regular study routines experienced greater benefits than those who used the center sporadically, suggesting that the impact of tutoring interactions is enhanced when engagement is consistent over time.

The authors also reported that tutors played a role in shaping students' ongoing help-seeking behaviors. Students who had positive, supportive interactions with tutors were more likely to return for subsequent sessions, whereas negative experiences could discourage future engagement. These findings indicate that each tutoring session contributes not only to immediate learning outcomes but also to the development of students' habits and attitudes toward academic support services.

Synthesis

The literature on what occurs during MLC visits portrays tutoring as a dynamic, interactive process. Schürmann et al. (2022) identified structured consultation phases, including diagnostic questioning, collaborative problem-solving, and reflective closure, that guide productive sessions. Grove and Croft (2019) and Wepner (1985) show that tutors themselves develop pedagogical expertise over time, moving from content-focused problem solvers to reflective facilitators who support student reasoning.

Student perspectives further highlight the importance of the social and emotional dimensions of tutoring. Duranczyk et al. (2006) found that students value MLCs as safe, supportive environments where they can ask questions without fear of judgment, while Tinsley et al. (2018) and Christiansen, Coxsey, and Moore-Russo (2022) demonstrate that tutor approachability, perceived relevance, accessibility, and consistency of engagement influence attendance and the benefits students derive from tutoring.

These studies indicate that the quality of tutoring interactions, shaped by both tutor development and session structure, interacts with student perceptions and engagement patterns to produce the learning, persistence, and confidence outcomes documented in the broader MLC literature. In short, the dynamics of tutoring interactions are a central mechanism through which MLCs generate their observed effects.

Limiting Studies

Despite extensive evidence supporting the effectiveness of Mathematics Learning Centers (MLCs), several studies highlight important limitations, inconsistencies, and areas for further investigation. Recognizing these constraints is essential for contextualizing reported outcomes and for informing data-driven improvements to center practices.

Dick (2016), in a case study at Oregon State University, found that although overall student outcomes in courses supported by MLCs were positive, patterns of student participation varied considerably across courses and demographics. Some courses showed consistently high engagement, whereas others experienced sporadic attendance despite high academic need. These findings suggest that MLC effectiveness is not uniform across an institution, but depends on course characteristics, student schedules, prior preparation, and the perceived value of support services. However, Dick's study was limited in scope and did not employ highly detailed data-analytic methods, highlighting the need for more granular, data-driven research.

Bannier (2007) examined predictive models of MLC attendance and identified multiple factors influencing participation, including prior mathematics achievement, course load, time constraints, and external obligations such as employment. These results indicate that usage patterns are shaped not only by academic need but also by extrinsic and personal factors, emphasizing that aggregate attendance metrics may obscure meaningful differences in student engagement.

Mills et al. (2022) conducted a national survey of mathematics tutoring centers in the United States, revealing substantial variability in services, staffing, assessment practices, and integration with academic departments. Some centers functioned primarily as drop-in labs, while others offered scheduled sessions or embedded course support. Similarly, Bhaird et al. (2009) documented differences across centers in resources, outreach strategies, and peer tutor training. This variability complicates cross-institutional comparisons of effectiveness and highlights the importance of considering context, resourcing, and implementation when evaluating MLC outcomes.

A related concern is limited performance assessment. Johns et al. (2023) note that many studies rely on improvements in grades or persistence without incorporating standardized, systematic measures across centers. Without robust metrics capturing both short-term outcomes and long-term behavioral changes, it is difficult to determine which components of MLC services are most effective or how centers might improve.

Behavioral limitations in the literature have also been identified. Navarro-Madsen and Ingram (2010) argue that simple aggregation of total hours or visits can mask nuanced engagement patterns predictive of student success. For example, students attending multiple short sessions may experience different learning benefits than those attending fewer, longer sessions, even if total time in the center is equivalent. The timing and regularity of visits may also influence outcomes. Granular data of this type are largely absent in existing research.

Taken together, these studies indicate that while MLCs are broadly effective, their success is contingent upon a complex interplay of student behavior, institutional context, service design, and assessment practices. Addressing these limitations requires research that integrates quantitative, qualitative, and longitudinal approaches, moving beyond simple measures of attendance to a more nuanced understanding of how MLCs support mathematics learning.

Synthesis and Conclusion

The collective findings from the literature, including both evidence of effectiveness and identified limitations, provide a comprehensive understanding of the role of MLCs in higher education. MLCs function as critical support mechanisms for students navigating the challenges of college-level mathematics, offering individualized guidance, peer collaboration, and structured opportunities for repeated practice and reflection. Across diverse studies, engagement with MLCs has been associated with higher grades, improved persistence, and increased student confidence.

Effective MLCs operate through multiple, interconnected mechanisms. Tutor–student interactions, structured problem-solving support, and the provision of psychologically safe environments are central to their impact. Kahu and Picton (2019) and Ali, Anwer, and Jaffar (2015) demonstrate that relational dimensions of tutoring, such as approachability, empathy, and investment in student success, can foster motivation, reduce anxiety, and encourage proactive help-seeking behaviors. These interactions contribute not only to immediate academic outcomes but also to the development of long-term study habits and self-efficacy, equipping students with skills that extend beyond individual courses.

Administrative and organizational factors are equally important. Cronin et al. (2025) and Menz and Jungic (2015) highlight the importance of embedding MLCs within departmental and institutional frameworks, aligning tutoring with curricular goals, and providing stable staffing and resources. Centers with trained tutors, clear performance assessment strategies, and institutional support are better positioned to deliver consistent, high-quality services. Wepner (1985) further emphasizes that investment in peer tutor training enhances both tutor and tutee outcomes, amplifying the overall effectiveness of the center.

Understanding patterns of student engagement is also crucial. While many studies report positive outcomes, reliance on aggregated metrics such as total visits or hours can obscure how students interact with MLCs. Navarro-Madsen and Ingram (2010) advocate for more granular analyses that consider visit duration, timing, and frequency. Such detail is essential for identifying which students benefit most, which services are most effective, and how centers can optimize operations to support diverse student populations.

Despite variability across institutions, courses, and student demographics, the evidence consistently demonstrates that MLCs provide meaningful value. They support struggling students, enhance the performance of average and high-achieving students, and contribute to the development of mathematical skills, confidence, and persistence. Limiting studies highlight areas for improvement, including the need for standardized assessment frameworks, nuanced analyses of engagement patterns, and careful attention to factors that influence participation and outcomes.

In conclusion, MLCs represent an evidence-supported intervention in higher education. They are most effective when integrated into departmental strategies, staffed with trained and reflective tutors, and structured to provide flexible, accessible, and supportive services. The literature suggests that future research should leverage detailed usage data, such as swipe-in/out records, session duration, and frequency patterns, to inform data-driven improvements and optimize the impact of MLCs on student learning and persistence.

Chapter 3
Theoretical Framework

Existing frameworks used in Mathematics Learning Center (MLC) research do not fully align with the analytical focus of this study. We will employ a framework for this study that analyzes the MLC as a retail store or a "storefront" for learning support. We will synthesize literature from organizational studies, retail analytics, operations management, and spatial theory to guide the empirical analysis of foot traffic, layout and flow, and service operations in an MLC.

Although academic support centers share broad goals such as improving persistence, strengthening disciplinary skills, and increasing academic confidence, MLCs are not interchangeable with centers such as a writing center or a chemistry learning center. Mathematics occupies a distinctive structural position in higher education. It is frequently a high-enrollment gateway sequence, it is tightly cumulative in prerequisite structure, and it is commonly associated with elevated levels of anxiety and performance pressure (Bailey, Jeong, & Cho, 2010; Hembree, 1990; DiGregorio & Hagman, 2021). These features shape not only whether students seek support but also when they seek it. Additionally, how long students remain in a center and whether demand concentrates into predictable congestion windows are also key aspects that have not received research attention. Thus, a framework attentive to flow, layout, and service operations is not merely a generic operational overlay, but a theoretically grounded response to the structural features of undergraduate mathematics.

Mathematics courses, particularly introductory mathematics, college algebra, and the calculus sequence often function as institutional gatekeepers. Research on community college and university pathways has consistently identified mathematics as a critical progression bottleneck, especially in early coursework (Bailey et al., 2010; McGee et al., 2021). Because these courses enroll large student populations and frequently determine advancement into major fields, demand for mathematics support is both high-volume and high stakes. This distinguishes mathematics centers from many other support environments that primarily serve upper-division majors or that assist with more project-based work that is not as synchronized to assessment cycles.

Mathematics learning is associated with well-documented affective barriers, particularly math anxiety. Hembree's (1990) meta-analysis established that mathematics anxiety is negatively correlated with performance and is linked to avoidance behaviors and heightened evaluative stress. Subsequent research (Ashcraft & Krause, 2007) has reinforced that mathematics anxiety influences help-seeking patterns, often producing concentrated engagement around assessment events rather than evenly distributed practice. In a drop-in tutoring environment, these affective dynamics can translate into observable traffic patterns, such as pre-exam surges and midweek demand clustering. These operational patterns are not incidental but instead reflect behavioral responses to the performance driven nature of mathematics.

The structure of mathematical problem-solving differentiates mathematics tutoring from many writing center models. Writing center research has historically emphasized nondirective consultation, iterative drafting, and dialogic engagement (North, 1984). In contrast, mathematics tutoring often requires real-time feedback, stepwise verification, and constrained solution processes. Recent research emphasizes the role of structured scaffolding and problem-focused interaction in supporting student learning (Alven et al., 2016). This difference in interactional structure has implications for session length variability, overlapping occupancy, and staffing density. In mathematics centers, sessions are frequently time intensive and require sustained step-by-step reasoning with validation of solutions, particularly near coordinated exam periods, which amplifies the relevance of service operations and queueing perspectives.

Our goal in this section is to present a framework that will assist in answering the following research questions that guide this study:

1. What is the overall attendance of the Math Learning Center, and how is that attendance distributed across different math courses?

2. What are the patterns of student attendance at the math learning center, and how do these patterns vary depending on the time of the academic year and the specific math course?

3. What are the distinct attendance patterns of individual students at the math learning center, and what course and temporal factors correspond to these patterns?

4. How does the attendance of the math learning center during early coursework impact students' future math learning center attendance?

5. What optimizations in staffing and services might be implemented based on student attendance patterns?

When going through our results, we will break down how we addressed each of these questions. For now, these questions should be kept in mind considering the theoretical framework we now present.

As previously alluded to, the goal again of the framework is to assist in answering these questions in a rigorous way. Therefore, we will begin defining what is meant by a "store" in this context. Then we situate the MLC in the context of non-profit organizational structure following the same ideas seen in the study by Johns et al. (2023) showing both parallels to commercial retail and relevant departures. Next, we review the three lenses employed: foot traffic analysis, store layout and flow theory, and service operations management. Finally, we articulate how these lenses coherently combine to lead to concrete propositions and hypotheses for this study.

What is a "Store"?

A retail store is a physical outlet where goods or services are exchanged between seller and buyer. The seller organizes physical space, marketing, staff, and service operations to influence consumer behavior (e.g., foot traffic, time spent, purchase decisions). The key here is the exchange between seller and buyer. In our context, the seller will include the tutors and the Math Center staff. They are "selling" their tutoring service to the students who are "buying" into the tutoring.

A non-profit educational center like the MLC does not sell goods in the market sense, but it offers services (e.g., mathematics tutoring, assistance, study space) to "customers" (i.e., students). The relationships among the stakeholders (e.g., students, peer tutors, staff, faculty) mirror those in a store including the supply of service, demand by students, staffing of employees, resource allocation, spatial organization, scheduling, and usage patterns. Even though profit is not the motive, many of the operational goals such as efficient resource utilization, maximization of space allocation, responsiveness to demand are analogous.

Johns and colleagues (2022) argue that MLCs can be viewed through the lens of non-profit organizational structures. These centers often have mission-driven goals (e.g., student success, retention), constrained resources (e.g., budget, staff, space), and operational challenges that align with non-profit literature including volunteer versus paid staff, funding streams, and stakeholder expectations.

Therefore, from the literature we noted some important qualities about non-profits and how they arise in consideration of an MLC. Non-profits often balance serving a high volume, often underserved population, while maintaining quality. In retail, this mirrors balancing foot traffic, for those most in need of the goods and services, and operation quality. Additionally, non-profits are often working under limited budgets, variable funding, and physical space constraints. This is important for analyzing staffing, scheduling, and spatial layout. Finally, non-profits may have less centralized control than a for-profit organization. This leads to more variation in policies, which can influence the consistency of its operation. This aligns with commercial stores having to follow franchise mandates. There are elements outside the control of the store but still they are aspects to which it must adhere. This corresponds to MLCs having to tutor certain subjects, be in available university spaces, and working with limited resources. An MLC is not a store in the commercial sense, but like an actual store, its constraints and mission shape what is feasible in terms of its staffing, advertising, opening times, etc. Thus, any theory borrowed from retail or operations must be adapted with awareness of non-profit reality.

MLC as a Retail Store

Since MLCs have been treated as non-profit entities in previous MLC research, it is not realistic to view the MLC as a retail store. In doing this we can draw on existing theoretical frameworks from retail store analysis and apply them to MLC research. The following table helps outline how an MLC acts in ways like a retail store.

Table 3.1

Operational Comparison of Retail Store Elements and Mathematics Learning Center Structures

Elements of Retail Stores	Analogue in Mathematics Learning Centers
Foot Traffic and Demand: Foot traffic, customer volume, visit patterns	Student visits, frequency, timing, and duration of use
Layout and Flow: Store layout, aisles, departments, spatial organization	Room layout, course-specific areas, and student movement between spaces
Service Operations: Staffing, scheduling, service delivery systems and resource allocation	Tutor scheduling, room assignment, queue management, and allocation of instructional resources

Table 3.1 allows us to see the relevancy of using the analogy of an MLC as a retail store. Now we move to the more specific theoretical lenses incorporated for this study.

Theoretical Lenses

Foot Traffic Analysis

Foot traffic (or store traffic) refers to the number of people entering or moving through a space over time. For retail stores, foot traffic is analyzed to understand customer volume, flow patterns, dwell time, conversion rates, etc. Some metrics that are used are the number of customer entries to the space, the amount of time dwelling in the store, repeat visits, path patterns and flow densities. Some of these metrics are applicable to MLC data for student visits.

In their 2010 paper, Anic, Radas, and Lim quantify how both the volume of traffic and how that traffic flows spatially (which paths customers take) affect how much shoppers spend. This is relevant, even though students do not spend money, they dedicate another currency, time. This is the students' investment with the benefit being learning. Thus, analogous metrics include time spent, academic gains, and satisfaction. From the data, we can analyze and look at time spent during students' visits, in relation to future visits. A study by Zhou and colleagues (2024), titled '*A statistical study of the pedestrian distribution in a commercial wholesale centre based on the traffic spatial structure,'* studied pedestrian distribution, store configuration, access points, etc. and their impact on how people move through large interior spaces. This is useful for understanding spatial exposure, and how areas of a space connect, and to predict which areas are used.

This is relevant to data on students' visits to MLC, especially for an MLC that has dedicated certain areas to different purposes (e.g., areas that provide tutoring for certain courses).

That allows measurement of foot traffic, including the number of visits per time interval, the temporal patterns (based on day of the week and time of day), and the frequency per student. We can also track flow through space, including which areas are visited, the times of congestion, and the distribution of occupancy.

Store Layout & Flow Theory

Store layout refers to the physical arrangement of space, including how rooms, sections, aisles, entrances, and exits are organized. Flow refers to the movement patterns of customers through that layout. This analyzes the ideas of natural flow paths, forced flow, exposure, congestion, wayfinding, visibility, and proximity. The idea is to maximize exposure to service offerings versus minimizing unnecessary distance thereby balancing open versus one-way paths and strategic placement of high-use services near entrances. Again, we will consider this application for MLCs, and our data can help address many of these ideas.

In their 2021 study by Pantano and colleagues used simulation to test how different space layouts impact consumer density, congestion, and exposure. Although the physical space of an MLC is typically fixed, it can inform where students might get stuck or avoid certain rooms. This information can help in how MLC leaders designate the use of different areas of their MLCs. A study by Hwangbo et al. (2017) used data from sensors to see how people move and which paths are most traveled, to inform layout changes or signage. While Urban (2022) studies how forcing directional flows influences customer behavior, exposure, path length, congestion. The idea is, if we see certain Math Center rooms avoided, we might have an issue through the layout and flow of an MLC. Also, room usage analysis can help determine if students having exposure to other classes and if they will be moving in a logical flow in an MLC when they take subsequent mathematic courses.

Even though an MLC layout is typically fixed (i.e., cannot easily change walls or available furnishings without significant financial investment), there are still many layout decisions and flow-related levers. For example, consider placement of services, in other words, which rooms host specific class tutoring. Other decisions relate to the proximity of these rooms to main entrance or high-traffic corridors and the scheduling of usage by rooms. At different times, some rooms may be low in usage while others may be high. These questions can be addressed by visitation data analysis.

Although the physical footprint of an MLC is typically fixed, the functional use of the space is adaptable. Administrators may reassign rooms, shift where courses are supported, or reorganize service areas in response to perceived traffic patterns or demand. This distinction between fixed structure and flexible usage is important for understanding flow, as it suggests that meaningful changes in congestion, visibility, and movement can occur without structural renovation. As such, layout and flow in MLCs should be understood not only in terms of physical design, but also in terms of how space is administratively designated and reconfigured over time.

Service Operations Management Theory

Service operations management encompasses how service entities (e.g., learning centers, tutoring centers, retail stores) manage resources (e.g., staff, schedule, space) to respond to demand, manage wait times, ensure service quality, and resource optimization. This analysis relates staffing to temporal distributions of students visiting an MLC.

Pei and colleagues (2020) analyzed how service offerings, layout, and staff distribution influence customer flows, leveraging indoor positioning to study movement patterns. While Guidotti et al. (2018) studied how customer behavior patterns over time (e.g., daily, weekly cycles, seasonal) can be detected and how operations (i.e., opening hours, staffing) can adapt to them.

All the above directly support the viewpoint of an MLC as a retail store. MLC resources are the tutors, the rooms in which tutoring occurs, the support staff, the scheduling policies, and advertising mechanisms of an MLC. The demand varies by time, by the type of help and subject area. Some constraints include the budget for staffing, staff availability, and space available. Understanding the interplay of these ideas helps understand an MLC data. In turn, use of data to understand the aspects of an MLC could help that MLC's staff can make more informed, more efficient decisions.

These mechanisms connect directly to the theoretical lenses adopted in this study. Foot traffic analysis is relevant; demand can be temporally clustered by weekday, by hour, and even around assessments (e.g., coordinated midterm exams that create predictable surges). Store layout and flow theory applies and is relevant when a MLC is organized into course-linked room areas, meaning that space allocation is structurally tied to curricular grouping. Service operations management is relevant because tutoring is time-intensive and variable in duration; staffing pressure is driven by overlapping visits and sustained occupancy, not solely by arrival counts. In this way, the operational framing is a logical lens to consider MLC concerns since it provides a measurable window into how students participate in and respond to the structure of undergraduate mathematics coursework in relation to MLS use.

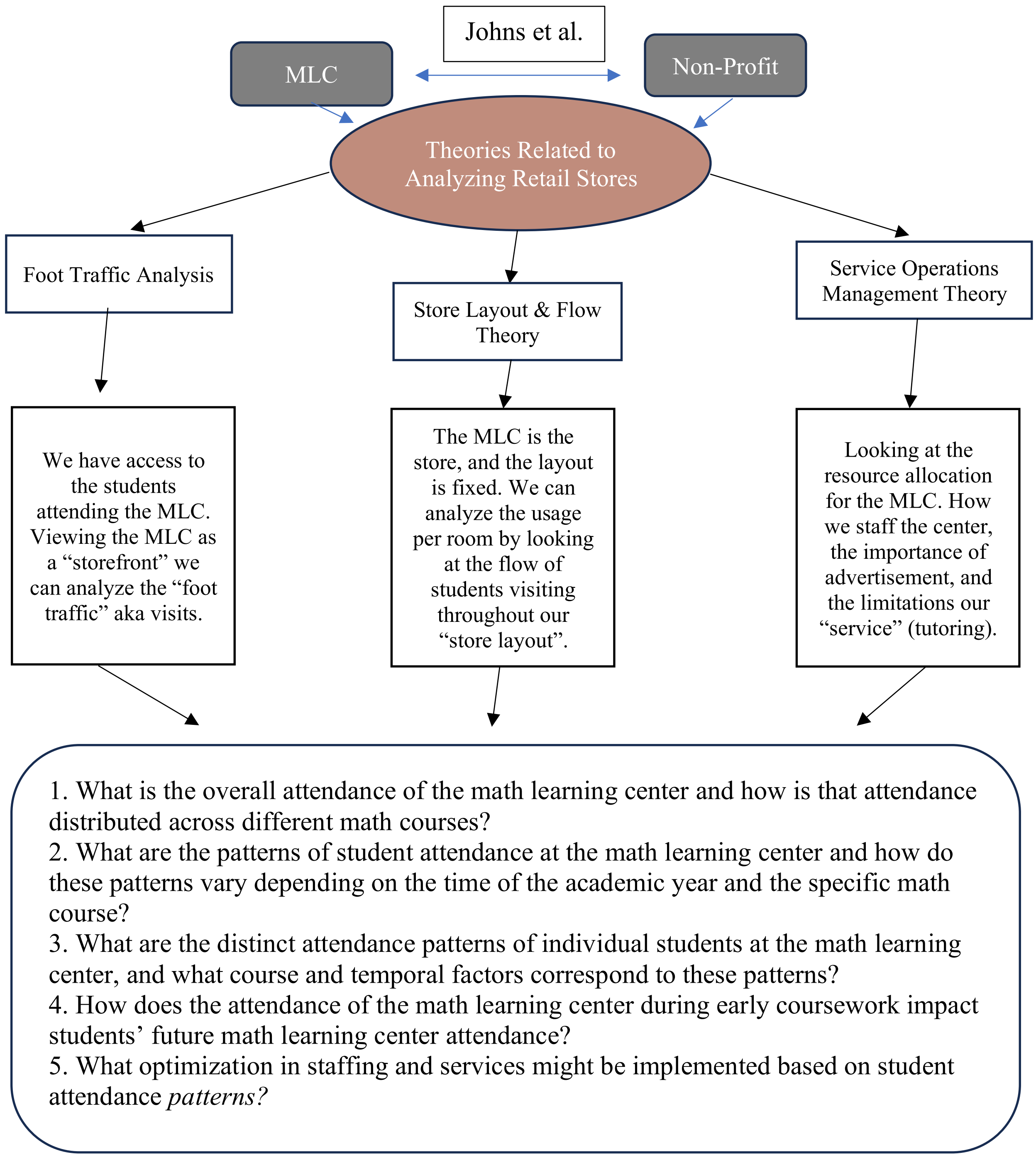
Finally, viewing an MLC through this lens does not replace mathematics education theory with logistical information. Informal mathematics learning relates directly to formal mathematical learning. So, studies such as this one that treat attendance patterns, repeat engagement, and exam alignment as behavioral traces of participation in a mathematical learning support are relevant to the research community in undergraduate mathematics education. Elevated demand in specific courses or time windows may signal curricular bottlenecks, assessment pressure, or cumulative conceptual load. Thus, the integration of organizational and service theory strengthens, rather than dilutes, the mathematics education contribution of the study by linking institutional support patterns to documented structural characteristics of undergraduate mathematics.

The subsequent methods sections situate these theoretical perspectives within a specific MLC context, where these concepts are operationalized through observed patterns of student visitation and space utilization.

Overall, these theories directly impact how we view the MLC, and the following flow chart easily shows how our thought process in using this framework:

Figure 3.1

Flow Chart of Theoretical Framework



Chapter 4
Methodology

The purpose of this chapter is to describe in detail the methodological approach used to examine student traffic, spatial flow, and service operations within an MLC at the university in our study. The methodology documents each stage of the process, from data acquisition and cleansing to data preparation, visualization, and statistical exploration.

This approach is grounded in the theoretical framework introduced in the previous chapter section, which positions an MLC as an analogue to a retail store. Accordingly, the data-driven analyses align with three interrelated theoretical lenses: Foot Traffic Analysis, Store Layout and Flow Theory, and Service Operations Management Theory.

The primary objective of the methodological design employed is to establish a transparent and reproducible process for examining patterns of student visitations within an MLC. The procedures ensure that all data used are accurate, de-identified, ethically handled, and suitable for quantitative analysis.

Data Source

The dataset analyzed in this study was provided by the Director of the Mathematics Tutoring Center at the University of Oklahoma (henceforth called the "Math Center") for Fall 2023 through Fall 2025. The unit of analysis in the dataset represents a single student check-in session, documenting when and where a student accessed services and for what subject.

Prior to analysis, all personally identifiable information was removed to maintain confidentiality in accordance with institutional ethical standards. A unique identifier was constructed for every individual using a combination of internal fields including the student's official university identification number, name, and university email address. These identifiers were then replaced with sequential numeric codes beginning at 1.

This approach allowed the research team to preserve a mechanism for quality assurance. If an anomaly was discovered (e.g., a tutor erroneously appearing as a student), the sequential identifier could be reported to the Director, who could cross-reference it privately to verify or correct the record without exposing personal information. After verification, all identifying data were permanently stripped from the analytic files. The following section provides descriptions of the structure and key variables of the dataset used in this study.

Data Description

The dataset consists of student check-in records collected across multiple semesters. The original data were organized by semester and contained the following variables:

- Check-In/Out Date
- Check-In/Out Time
- Total Minutes (Duration of Stay)
- Student ID (This is the unique de-identified identifier used for the person entering.)
- Category of Person Entering the Math Center (Student, Tutor, Front Desk Worker)
- Subject (Includes Course Number and Description)
- Location

Most of the variables are straightforward with the exception being the Subject. The Subject variable identifies the specific course associated with each student visit and is central to the course-level analyses conducted in this study. Subjects are recorded using official university course numbers and titles. To ensure clarity in interpretation, the primary courses represented in the dataset are listed below.

Table 4.1

Mathematics Courses Represented in the Dataset

Course Number	Official Course Name
MATH 1005	Mathematical Reasoning
MATH 1473	Mathematics for Critical Thinking
MATH 1503	College Algebra
MATH 1523	Pre-Calculus and Analytical Geometry
MATH 1643	Functions and Modeling
MATH 1743	Calculus I for Business, Life and Social Sciences
MATH 1823	Calculus and Analytical Geometry I
MATH 1914	Differential and Integral Calculus I
MATH 2113	Mathematical Systems
MATH 2223	Data Analysis and Geometric Systems
MATH 2423	Calculus and Analytical Geometry II
MATH 2433	Calculus and Analytical Geometry III
MATH 2443	Calculus and Analytical Geometry IV
MATH 2924	Differential and Integral Calculus II
MATH 2934	Differential and Integral Calculus III
MATH 3113	Introduction to Ordinary Differential Equations
MATH 3333	Linear Algebra I
MATH 3413	Physical Mathematics I

Several courses are commonly referred to by alternative names or serve distinct structural roles within the undergraduate mathematics curriculum. MATH 1005 (Mathematical Reasoning) is considered a developmental mathematics course and was incorporated into the mathematics department beginning in Fall 2025. MATH 1523 (Pre-Calculus and Analytical Geometry) is often referred to as College Trigonometry, while MATH 1643 (Functions and Modeling) is commonly known as Business Pre-Calculus. Similarly, MATH 1743 (Calculus I for Business, Life and Social Sciences) is frequently referred to as Business Calculus.

In addition to naming conventions, several courses form structured calculus sequences. The courses MATH 1823, 2423, 2433, and 2443 comprise a four-semester sequence in calculus and analytical geometry. Alternatively, MATH 1914, 2924, and 2934 form a three-semester sequence of differential and integral calculus. These distinctions are important for interpreting patterns of student progression and demand across course groupings.

Individual semester files were merged sequentially into a single master spreadsheet. This produced a unified dataset of 69,334 units suitable for import into R for cleaning and analysis. An additional variable, Semester, was manually inserted into each file to mark the term associated with each unit of analysis.

Data Cleansing

After importing the data into R, date and time fields were standardized for machine readability. Original entries varied in format and were incompatible with R's default date-time classes. Dates were converted to ISO-compliant formats, and times were reformatted to a 24-hour clock. A combined Datetime field was created to streamline time-based computations such as session duration and hourly aggregation.

Using R functions, Check-In and Check-Out timestamps were decomposed into Month, Day, Year, and Weekday. This decomposition enabled finer analysis of visit frequency across days and weeks, aligning with Foot Traffic Analysis theory, which emphasizes identification of temporal cycles in customer flow.

To ensure data integrity, several diagnostic flags were created:

1. Cross-Date Flag: Identified sessions where Check-In Date ≠ Check-Out Date. Since the Math Center does not operate overnight, such records likely reflected missed sign-outs.
2. Duration Mismatch Flag: Compared computed duration (Check-Out – Check-In) with the reported Total Minutes field. Records differing by more than one minute were flagged to account for rounding or input errors.
3. Duplicate Flag: Detected identical combinations of key fields to eliminate double entries.
4. Short Session Flag: Marked sessions below a practical engagement threshold (less than 5 minutes), indicating accidental or incomplete sign-ins.

Incomplete subject data were addressed using an inferential approach. If a student consistently attended sessions for the same course (e.g., College Algebra) throughout a semester, but one or more sessions lacked a subject entry, those missing fields were inferred to match the student's dominant course pattern. This maintained internal consistency without artificially inflating or reducing course-level attendance counts, like demand forecasting in retail analytics.

We decomposed the Subject field into three analytic components:

- Type: the disciplinary prefix (e.g., MATH)
- Number: the catalog course identifier (e.g., 1503)
- Description: the course title (e.g., College Algebra)

Because the Math Center is physically divided into color-coded areas (called "rooms"), spatial attributes were mapped to those colors to operationalize the Store Layout and Flow construct. Each room's color corresponds to specific course-levels.

Table 4.2

MLC Room Color and Associated Class Number

Room Color	Course Grouping
Orange	MATH 1473, 2113, 2223, 1005 (in FA25)
Yellow	MATH 1503 & 1523
Green	MATH 1634, 1743
Blue	MATH 1824, 1914, 2423
Red	MATH 2433, 2443, 2924, 2934
Purple	MATH 3113, 3333, 3413
Grey	Miscellaneous or Unspecified

Analyzing visitation by room color enabled examination of spatial distribution, comparable to zone analysis in retail stores where departments differ in customer draw and density. Therefore, an additional column of information was added to each data unit to address the room color the student attended.

Several new variables were generated to enhance interpretability. The first was Time-of-Day Category: Morning (before 12:00), Afternoon (12:00–17:00), or Evening (after 17:00) sessions. This supports examination of diurnal usage patterns consistent with Foot Traffic Analysis. The second was Visit Summary Metrics where for each unique visitor the following were noted: first visit date, last visit date, and total number of visits.

Once cleaning, transformation, and flagging were complete, all derived variables were merged into a final master dataset. No records were deleted at this stage, leaving a total of 35,529 units to be used for analysis. Additionally, we made sure flagged observations were retained for transparency and potential sensitivity analysis. The final dataset was exported as a comma-separated values (CSV) file, ensuring interoperability for replication and archiving.

Data Analyses

Analyses were conducted in R using core and supplementary libraries, including tidyverse for data manipulation and ggplot2 for visualization. Each research question and sub-question was operationalized through dedicated R scripts. Visualizations (including bar charts, heat maps, density plots), enabled exploration of spatial and temporal usage patterns, consistent with Foot Traffic and Store Layout frameworks, while summary statistics and comparative plots (e.g., by room color or time) supported Service Operations insights regarding staffing and capacity.

To support these analyses, a range of visualization techniques and statistical methods were employed, selected based on the structure of the data and the research question of interest. Bar graphs and stacked bar graphs were used to display counts, proportions, and distributions of student visits across categorical variables such as course, room, and day of the week. These visualizations allowed for both direct comparisons and proportional breakdowns of attendance patterns. Line graphs were used to illustrate temporal trends, including changes in visitation across weeks of the semester. Heat maps were used to represent the intensity of attendance across combinations of time (e.g., hour of day and day of week), providing a clear visual representation of peak usage periods. Tables were used throughout to present precise numerical summaries where exact values were necessary for interpretation.

Box plots were used to examine the distribution, spread, and central tendency of numerical variables such as session duration and visit frequency, and to facilitate side-by-side comparisons across courses and room groupings. Empirical cumulative distribution function (ECDF) plots were used to assess the cumulative proportion of observations below given thresholds, particularly useful for understanding visit frequency and duration patterns. Density plots were used to examine the shape and clustering of continuous variables, including principal component analysis (PCA) density visualizations to explore underlying structure in multivariate data.

Summary statistics including means, medians, ratios, percentages, and normalized utilization measures were used to quantify patterns observed in the data. Normalized utilization was defined as the proportion of enrolled students who visited the MLC within a given course and semester, allowing for comparisons across courses with differing enrollment sizes.

For modeling and inferential analysis, negative binomial regression was employed to model count-based outcomes with overdispersion, particularly in examining visit frequency across courses and semesters. Receiver Operating Characteristic (ROC) analysis was used to evaluate the performance of classification models, particularly in predicting student return behavior. Cluster analysis techniques were used to identify distinct patterns of student engagement based on visit frequency, timing, and duration. Sankey plots were used to visualize transitions or trajectories in student behavior over time, providing insight into patterns of progression.

To quantify differences in tutoring demand across courses while accounting for variation in enrollment size, a count-based regression framework was employed. Visit counts were aggregated at the course-semester level and modeled using a generalized linear model (GLM) approach with a log link function. Because courses varied substantially in enrollment, the logarithm of enrollment was included as an exposure offset in the model. This specification allowed visit counts to be interpreted as rates per enrolled student rather than raw totals, enabling meaningful comparisons across courses of different sizes.

The expected number of visits for a given course–semester combination was modeled as a function of course and semester indicators, with enrollment acting as a scaling factor. Incorporating the offset ensured that the model estimated relative utilization intensity rather than absolute volume, preventing large-enrollment courses from dominating the analysis solely due to scale.

A Poisson regression model was initially considered as a baseline approach for modeling count data. However, the Poisson distribution assumes equidispersion, meaning that the variance of the outcome is equal to its mean. Preliminary examination of the data suggested that this assumption was unlikely to hold, as tutoring participation exhibited substantial variability across students and courses.

To formally assess dispersion, the Pearson Chi-square statistic divided by its degrees of freedom was computed. The resulting dispersion ratio of 45.74 indicated substantial overdispersion, with the variance far exceeding the mean. This level of dispersion violates the assumptions of the Poisson model and can lead to underestimated standard errors and inflated statistical significance.

Given this violation, a Negative Binomial regression model was adopted. The Negative Binomial specification extends the Poisson model by introducing an additional parameter that allows the variance to exceed the mean. This flexibility makes it more appropriate for modeling overdispersed count data and provides more reliable inference in the presence of heterogeneous participation patterns.

Model coefficients were exponentiated and interpreted as incidence rate ratios (IRRs). These ratios represent multiplicative differences in expected visit rates relative to a reference category, allowing for straightforward interpretation of relative tutoring demand across courses and semesters.

These visualization and statistical techniques were selected to align with the study's objectives of understanding both aggregate attendance patterns and individual-level engagement behaviors, ensuring that each method appropriately matched the structure and purpose of the data being analyzed.

To characterize the distribution of student visit frequency, the empirical cumulative distribution function (ECDF) was used. The ECDF provides a cumulative representation of the proportion of observations that fall at or below a given value. In this context, it was used to quantify the proportion of students who visited the Math Learning Center (MLC) at or below a specified number of times within a semester.

Unlike histograms or frequency tables, which display counts within discrete bins, the ECDF represents the full cumulative distribution of visit counts. For any given value, the ECDF corresponds to the proportion of student–semester observations with the given value or fewer visits. This allowed for direct interpretation of thresholds in student engagement (e.g., the proportion of students who visited at most three times).

The ECDF was selected because it provides a clear and interpretable representation of how participation accumulates across students without requiring arbitrary binning decisions. It also facilitates identification of natural breakpoints in engagement behavior, supporting the classification of students into usage categories such as one-time users, occasional users, and high-frequency users.

To avoid arbitrary threshold selection, cutpoints were anchored to the empirical distribution of the dataset. High-frequency engagement was defined as total visits at or above the

90th percentile of the observed distribution. Frequent usage corresponded to visits at or above the 75th percentile. Long-session engagement was defined as mean minutes per visit at or above the 75th percentile. These thresholds were computed directly from the observed data and reported in the summary output to ensure transparency and reproducibility.

By defining high-intensity groups relative to the observed distribution rather than imposing external standards, the classification remained descriptive of actual participation patterns within the MLC. This approach ensured that usage categories reflected the behavioral structure of the dataset and were directly interpretable within the operational context of the center.

To examine factors associated with student return behavior, a series of logistic regression models were estimated. Logistic regression was selected because the outcome of interest, whether a student returned within the semester, was binary. This approach allows estimation of the probability of return as a function of multiple predictors while controlling for potential confounding factors.

To isolate the effects of temporal engagement patterns from overall usage intensity, models included controls for the total number of visits and total minutes spent in the Math Learning Center (MLC) during the semester. These variables captured the magnitude of engagement and ensured that timing-related effects were interpreted independently of overall usage levels.

A semester index variable (SemIndex) was included to account for longitudinal variation across semesters, capturing potential shifts in usage patterns over time. In addition, course-sequence context was incorporated through pipeline stage indicators, allowing the models to account for differences associated with students' progression through the curriculum.

To address the non-independence of observations arising from repeated student participation across semesters, cluster-robust standard errors were applied at the student level. This adjustment accounts for within-student correlation and provides more reliable inference.

Model specifications were constructed incrementally to evaluate the contribution of different predictor sets. The baseline model included timing and semester controls. Subsequent models introduced engagement intensity measures, followed by course-sequence indicators. A final model included an interaction between early-semester engagement and visit frequency to assess whether the relationship between timing and return varied across levels of usage intensity.

The Math Center hosts “After Dark” events (evening review sessions and tutoring) prior to major exams, during which attendance surges dramatically. Because these sessions differ qualitatively from normal operations, analyses were performed both with and without After Dark data. This dual analysis provided a clearer understanding of baseline operational flow, analogous to separating promotional-event sales from regular sales, in retail analytics.

Data validation involved iterative review of flagged records and cross-checking aggregated statistics against expected operational norms. Random samples were inspected manually to verify that automated transformations performed as intended. Through this process, the study ensured fidelity between raw attendance logs and the analytic dataset.

Limitations

1. Observational Nature: The study relies on existing operational data; no experimental manipulation was introduced.
2. Spatial Resolution: While room-level data approximate layout analysis, precise path tracking (e.g., via indoor sensors) was unavailable.

3. Missing Contextual Variables: Although overall tutor staffing levels were available, detailed information on tutor assignments to specific rooms or courses was not fully integrated into the dataset. This limited the ability to evaluate how staffing was distributed relative to student demand within different areas of the MLC.
4. Inferred Values: In some cases, session records were missing subject information. When a student consistently attended sessions for a single course within a semester, missing subject entries were inferred based on that student's dominant course pattern. While this approach preserved consistency in course-level analyses, it introduces a small degree of uncertainty, as inferred values may not perfectly reflect the true course associated with every session.

These limitations are typical of real-world operational datasets and are acknowledged in interpreting results.

Chapter 5
Results

In this section, we address the five primary research questions articulated previously. Each of these overarching questions was further refined into a series of targeted sub-questions designed to guide the empirical investigation and ensure comprehensive use of the available data. These sub-questions functioned as analytic pillars, structuring the presentation of findings and clarifying the logical progression from data exploration to substantive conclusions.

The results are presented using a systematic and methodical approach to ensure thorough coverage of each research objective. For each primary research question, we conducted a focused, micro-level analysis that examined the relevant variables, patterns, and statistical relationships in detail. This approach allowed for precise interpretation of course-level, room-level, and attendance level dynamics as appropriate to each question.

Following the completion of these individual analyses, a broader synthesis is provided in the subsequent section. This macro-level analysis integrated findings across research questions, highlighting overarching trends, interrelationships, and institutional implications that emerged from the collective results.

Attendance Distribution Data

Recall the first research question guiding this analysis was:

What is the overall attendance of the Math (Learning) Center, and how is that attendance distributed across different mathematics courses?

This question sought to establish a foundational understanding of usage patterns within the Math Center. Specifically, it examined not only the aggregate level of attendance but also how that attendance was distributed across courses. By doing so, the analysis provided insight into which courses generated the greatest demand for tutoring services and how student engagement varied across the curriculum.

To address R1 in a comprehensive and analytically rigorous manner, several sub-questions were developed. Attendance data can be interpreted in multiple ways, and relying on a single metric would provide only a partial representation of student utilization. Therefore, this section examined attendance through multiple complementary lenses.

First, we analyzed which mathematics courses generated the highest number of unique student visits to the Math Center. Unique student visits reflect the breadth of course engagement, that is, how many individual students enrolled in each course were utilizing tutoring services at least once a semester. This metric captured the reach of the Math Center across the student population.

Second, we examined which mathematics courses account for the highest total number of student visits. In contrast to unique visits, total visits reflected overall demand intensity. A course may have a moderate number of unique student visits but a high number of total visits if students return frequently for support. This distinction allowed us to differentiate between widespread engagement and concentrated, repeated usage.

Third, we evaluated the proportion of student visits per course relative to total Math Center visits. This proportional analysis contextualized course-level attendance within the broader operational scope of the Math Center. By calculating the percentage contribution of each course to total visits, we were able to identify which courses disproportionately drive tutoring demand and which represented a smaller share of overall utilization.

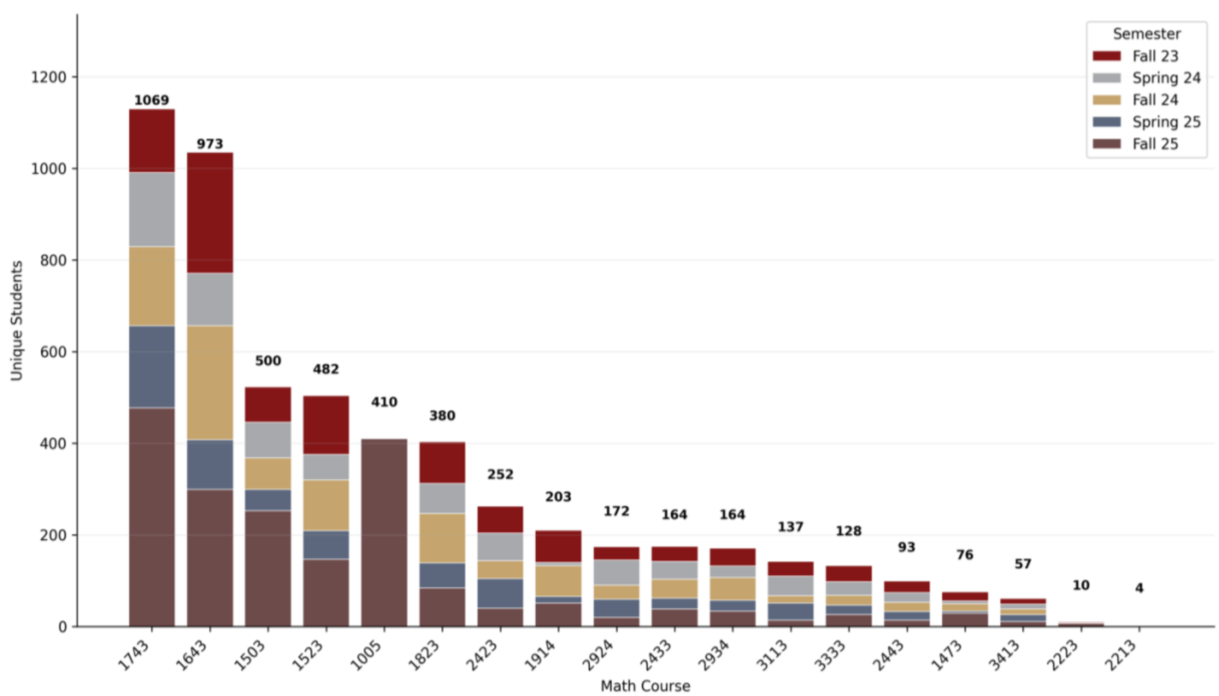
Finally, we considered utilization rates, which provided an additional layer of interpretation. Utilization rates allowed us to assess attendance relative to student enrollment (i.e., course size), offering insight into the intensity of support-seeking behavior within specific courses. This measure helped distinguish between high attendance driven by large enrollment and high attendance driven by elevated academic support seeking by students in a course.

Taken together, these sub-questions ensured that the first research question was addressed systematically and comprehensively. Rather than relying on a single descriptive statistic, the analysis used triangulation across multiple indicators: unique visits, total visits, proportional contribution, and utilization rates to develop a nuanced understanding of attendance distribution across mathematics courses.

We now begin by examining the number of unique student visits at the Math Center.

Figure 5.1

Stacked Bar Graph of Unique Math Center Visitors by Course and Semester



A unique visitor was defined as a student whose unique identifier code appears at least once in the Math Center attendance records during a given semester. Under this definition, each student was counted only once per semester, regardless of how many times the student visited the Math Center in the term. However, a student was counted again in a different semester if he or she utilized the Math Center in multiple terms. This operationalization ensured that the metric reflected the breadth of student engagement during a specific semester rather than frequency of repeat usage.

Analysis of unique student visitors by course across the full study period revealed that MATH 1743 and MATH 1643 exhibited the largest unique student populations, with 1,069 and 973 students, respectively. Both courses corresponded to offerings for business, life, and social science majors, which historically enroll a substantial proportion of students. Their prominence in unique visitation was therefore consistent with enrollment scale and reinforced the expectation that high-enrollment gateway courses would generate significant tutoring demand.

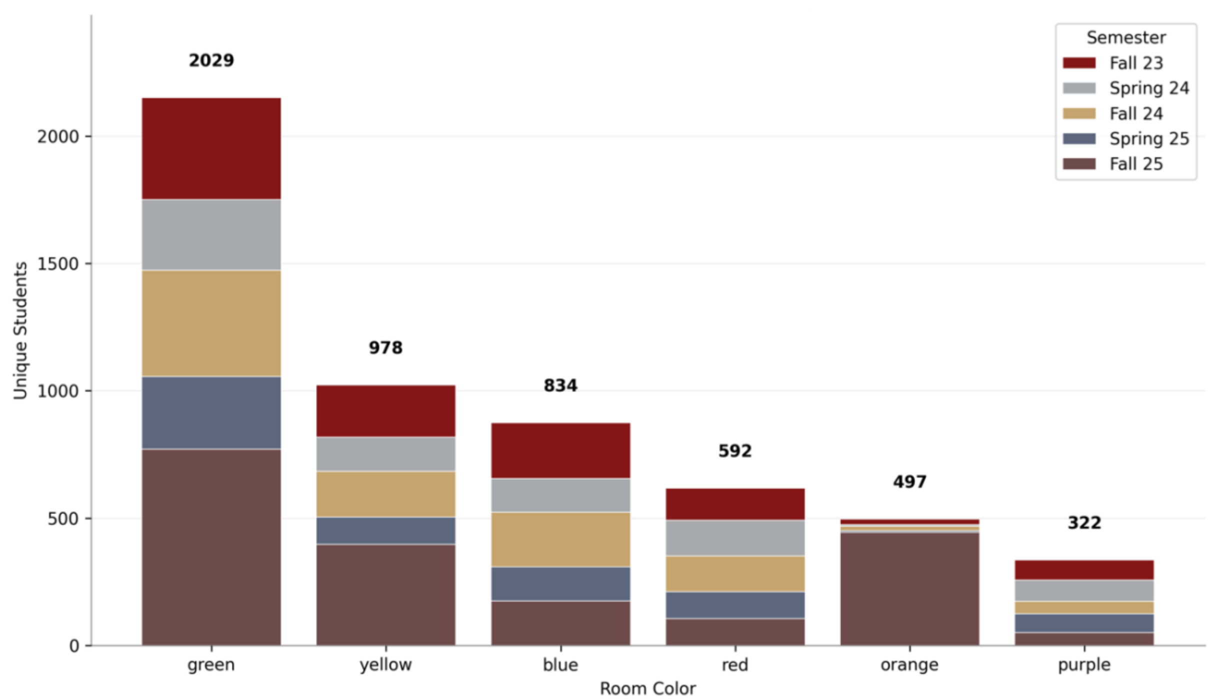
Additionally, MATH 1005 and MATH 1743 both experienced increases in unique student visits in Fall 2025. The increase in MATH 1005 is particularly noteworthy, as Fall 2025 marked the first semester in which this course was offered in the mathematics department, replacing what had previously been offered as developmental math through a community college partner. This structural change influenced visitation patterns.

Similarly, MATH 1743 underwent a change in course coordination in Fall 2025, including the implementation of a new textbook with a slightly different emphasis and a slightly revised assessment structure as well as a new course coordinator. Such curricular and assessment modifications may have contributed to increased academic support seeking behavior, potentially explaining the rise in unique visitors during that semester. These findings suggest that both administrative restructuring and instructional changes can impact students' utilization of tutoring services.

While course-level analysis provided important insights, the organizational structure of the Math Center necessitated further disaggregation. The Math Center operates across a series of connected spaces. The spaces are called rooms, and each is designated by color. Each room typically supports courses grouped in some logical arrangement according to students' majors and the level of mathematics being taught. Consequently, examining unique visitation solely by course might have obscured spatial and operational dynamics within the center. To better understand how student demand was distributed within the physical layout of the Math Center, it was therefore essential to analyze the distribution of unique visitors by room color (see Table 4.2). This additional layer of analysis allowed for a more comprehensive interpretation of resource allocation and operational efficiency.

Figure 5.2

Stacked Bar Graph of Unique Math Center Visitation Numbers by Room Color and Semester



Please note, room-level totals are calculated by summing course-level unique student counts within each room band. Because students may appear in multiple courses assigned to the same room, they may be counted more than once in the room-level totals. Therefore, these totals reflect cumulative course demand rather than distinct student counts and are not directly comparable to course-level values.

Consistent with the course-level findings, the distribution of unique visitors across room colors reflected the academic composition of the Math Center. The Green Room recorded the largest number of unique visitors, which aligns with the fact that it supports MATH 1743 and MATH 1643, both high-enrollment math courses for business, life, and social science majors. Given the substantial student populations in these courses, it was not surprising that the Green Room exhibited the highest number of student visits.

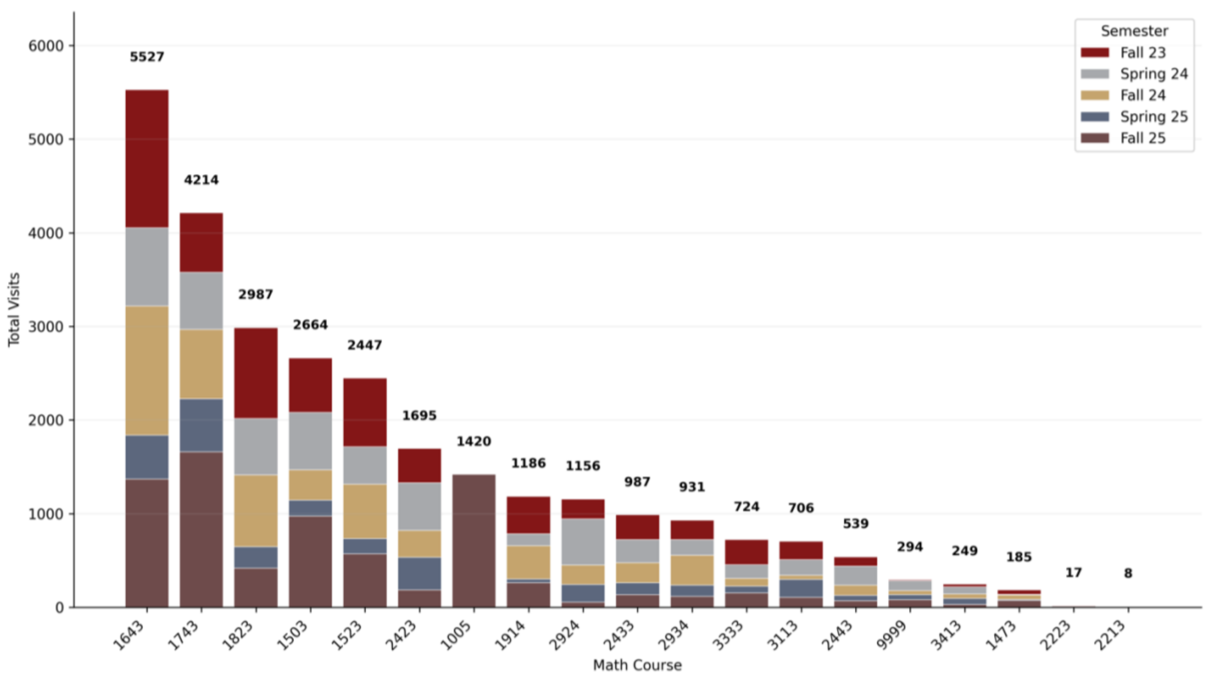
The Orange Room experienced a notable increase in unique visitors following the addition of MATH 1005 in Fall 2025. With the integration of this course into the mathematics department, the Orange Room subsequently outpaced the Purple Room in unique visitation counts. This shift underscored how structural and curricular changes at the departmental level can directly influence the spatial distribution of tutoring demand within the Math Center.

In contrast, the Red and Purple Rooms demonstrated comparatively lower unique visitation counts. These rooms primarily serve more advanced mathematics courses, which typically have smaller enrollment sizes. From a service theory perspective, this pattern was consistent with the expectation that courses with larger student populations generate greater aggregate demand for academic support services. Higher enrollment increases the probability that a larger number of students will seek tutoring assistance, thereby elevating visitation metrics.

However, unique visits only provide a partial understanding of Math Center utilization. While it captured the breadth of engagement (i.e., how many individual students access services), it did not account for the intensity of usage. A student who visited the Math Center once during a semester is weighted equally as a student who attended the Math Center weekly. Therefore, to fully assess operational demand and resource implications, it was necessary to also examine total visitation counts. Total visits provided insight into frequency of use and repeated engagement, offering a more comprehensive evaluation of the Math Center's workload and service demand.

Figure 5.3

Stacked Bar Graph of Total Math Center Visitations by Semester and Course Number



Before proceeding to the analysis of total visitation counts, it was again necessary to disaggregate the data by room color. As previously noted, the organizational structure of the Math Center is spatially defined, with courses assigned to designated color-coded rooms.

Consequently, overall visitation patterns cannot be fully understood without examining how total visits were distributed across these operational units.

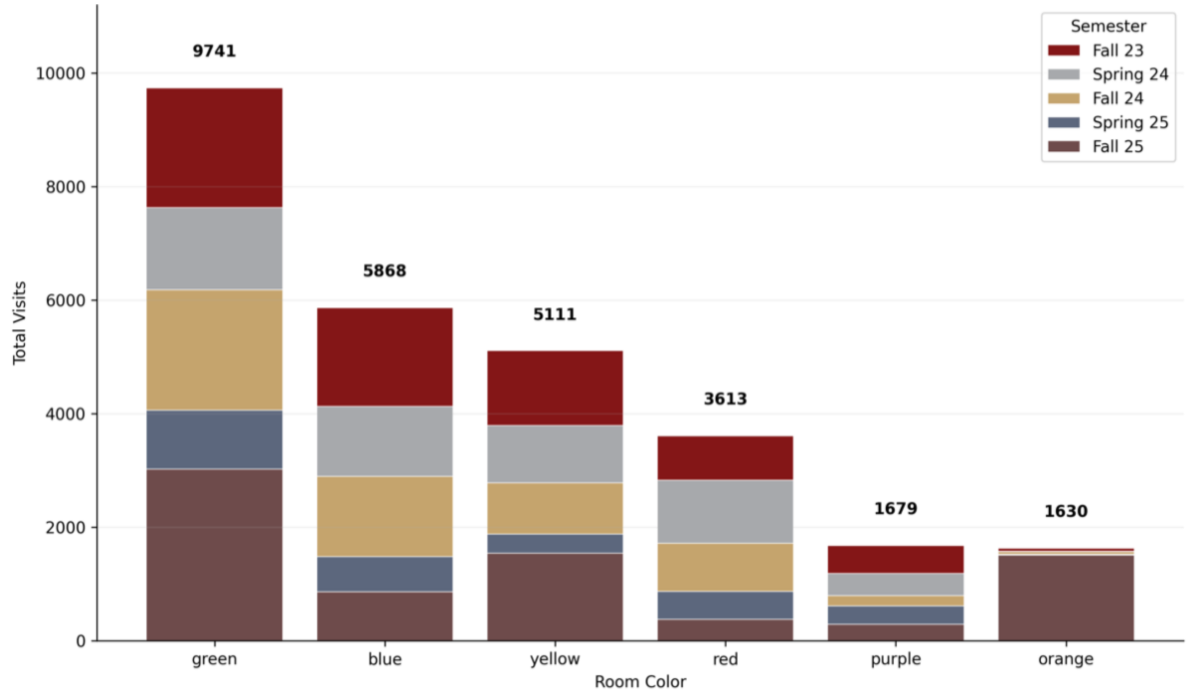
Analyzing room-level totals allows for a more precise evaluation of service demand within the physical infrastructure of the Math Center. While course-level analysis identified which academic offerings generated the greatest need, room-level analysis clarified where that demand materialized within the center. This distinction is particularly important when considering staffing allocation, tutor deployment, and space utilization.

Moreover, total visitation by room may reveal patterns that differ from those observed in unique visitation. For example, a room may not have the highest number of unique students but may nonetheless experience high total visits if its associated courses generate frequent repeat usage. Therefore, incorporating room color into the total visitation analysis ensured that both breadth (unique students) and intensity (repeat visits) were examined within the operational framework of the Math Center.

With this structure in place, we now turn to the total visitation data disaggregated by room color.

Figure 5.4

Stacked Bar Graph of Total Student Visits by Room Color and Semester



An examination of total visitation counts by room color indicated that the Green Room continued to account for the largest volume of visits, reinforcing its position as the primary driver of overall Math Center demand. This finding remains consistent with its association with high-enrollment courses, as previously acknowledged. However, a notable shift emerged when considering the Blue Room. While it did not dominate in unique visitation to the same extent as the Green Room, it demonstrated a substantial increase when total visits were considered.

This pattern suggests that students utilizing the Blue Room were returning at a higher frequency relative to other rooms. It raises an important comparative question: Are Blue Room students, on average, visiting the Math Center more frequently than students in classes served by other rooms? If so, this would indicate greater intensity of usage rather than simply broader reach. Such distinctions are critical for operational planning, as repeated visitation contributes more significantly to staffing demand and tutor workload than single-use attendance.

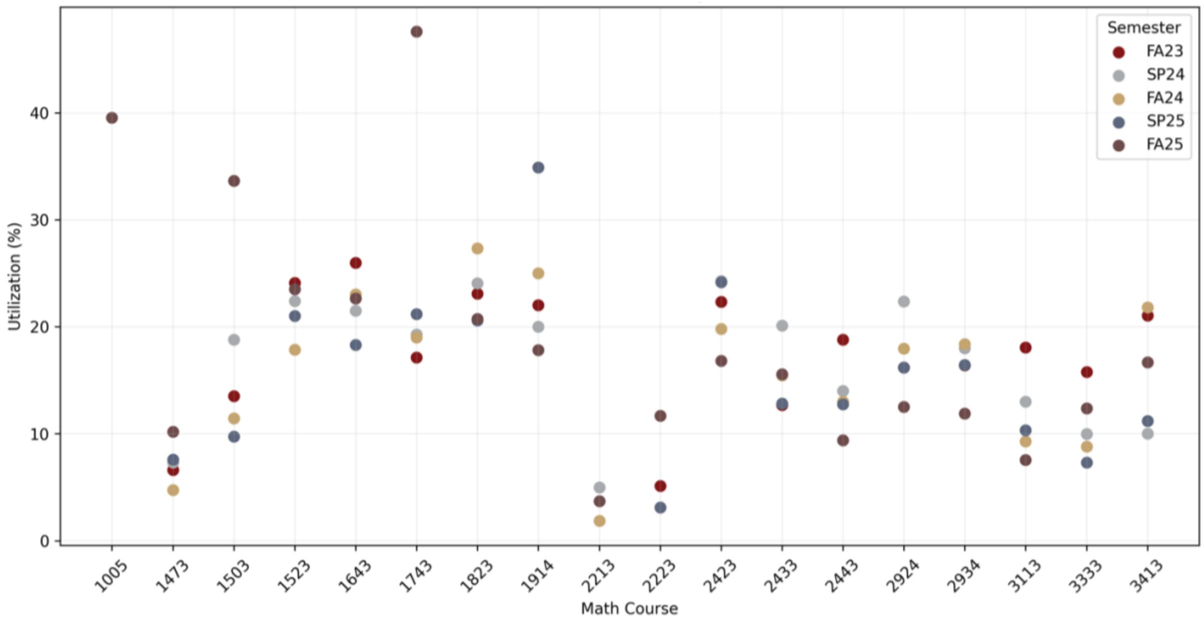
These observations align with the service-based theoretical framework guiding this study. The framework posits that attracting unique visitors represents the first stage of effective academic support engagement. However, sustained impact and operational significance are driven by converting those initial users into repeat visitors. In other words, breadth of engagement is necessary, but intensity of engagement ultimately defines service demand. The Blue Room's increase in total visits, relative to its unique visitation footprint, may reflect successful retention of tutoring users (i.e., students coming in for tutoring repeatedly in a semester) or heightened academic need within its associated courses.

While both unique and total visitation metrics are informative, neither alone could account for differences in course enrollment size. High visitation in a course with large enrollment could simply reflect scale rather than elevated support-seeking behavior. To address this limitation, we developed a metric referred to as the utilization rate. The utilization rate was defined as the number of unique student visitors divided by the total enrollment for the corresponding course. This measure standardizes visitation relative to class size, allowing for meaningful comparisons across courses with varying enrollments.

By examining utilization rates, we could assess which courses generate proportionally higher engagement with the Math Center, independent of raw enrollment numbers. Figure 5.5 displays the relationship between enrollment and unique visitation, providing insight into whether larger classes simply drive volume or whether certain courses demonstrated disproportionately high levels of tutoring engagement relative to their size.

Figure 5.5

Scatter Plot of Enrollment-Normalized Utilization by Course and Semester



Analysis of the utilization rates for the courses served by the Math Center reveals that Fall 2025 demonstrates the highest overall proportional student engagement with the center. More broadly, the data indicated that Fall semesters consistently exhibit higher utilization rates than Spring semesters. Within the context of the theoretical framework, this seasonal pattern may reflect variations in student needs at different points in the academic cycle. Fall terms often include a larger concentration of first-year and transfer students adjusting to institutional expectations, which may increase demand for structured academic support services. Additionally, course sequencing patterns may result in a higher concentration of gateway mathematics enrollment during the Fall, thereby amplifying proportional usage.

A particularly noteworthy finding is that MATH 1743 exceeded a 50% utilization rate in Fall 2025, making it the only course in the dataset to surpass this threshold during a semester.

This indicates that more than half of enrolled students in that course accessed the Math Center at least once, suggesting exceptionally high penetration of tutoring services.

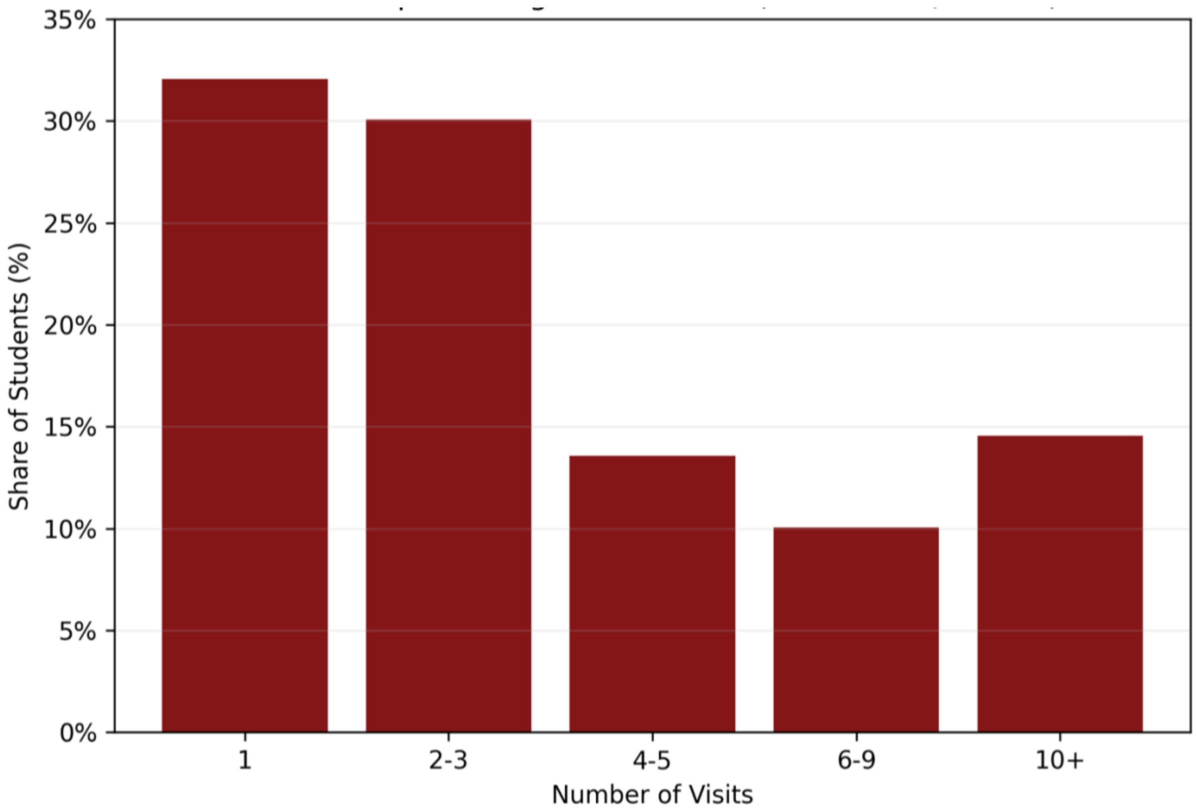
In contrast, advanced mathematics courses demonstrated lower and more variable utilization rates across semesters. While gateway courses exhibited relatively consistent patterns of engagement, upper-division courses showed greater proportional fluctuation. This variability may stem from smaller enrollment sizes, cohort differences, or varying instructors (and instructional approaches) across semesters. These structural distinctions are essential for understanding tutoring demand within the broader undergraduate mathematics curriculum. Gateway courses appeared to generate stable and predictable support needs, whereas advanced courses produced more episodic and enrollment-sensitive demand patterns.

Following the examination of utilization rates, the analysis turned to repeat visitation behavior. Whereas utilization captured initial engagement relative to enrollment, repeat visits distinguished episodic use from sustained participation. Understanding repeat behavior is critical for operational planning, as frequent users contribute disproportionately to total service demand.

To enhance interpretability, repeat visits were categorized into five bins according to the numbers of visits per semester: 1 visit; 2–3 visits; 4–5 visits; 6–9 visits; and 10 or more visits. This categorization allowed for differentiation between single-use participants and increasingly sustained levels of engagement. Importantly, isolating the 10+ visit category identified heavy users while preserving meaningful distinctions among moderate repeat behaviors. This structured approach provided a clearer understanding of the depth of student reliance on the Math Center beyond initial access.

Figure 5.6

Bar Graph of Repeat Usage Distribution of all Courses



When aggregating repeat visitation across all courses, the distribution reveals that most (about a third of) students attend tutoring only once a semester. However, a meaningful subset of students engaged in repeated visits, with a non-trivial proportion (~15%) classified as heavy users (10+ visits). This pattern indicated that tutoring demand is not evenly distributed across the student population. Rather, it reflects layered participation intensity, where a smaller group of students accounted for a disproportionate share of total service volume.

The prevalence of heavy users varied substantially across courses. Courses with elevated proportions of students in the higher visit bins may signal structural academic challenges, such as cumulative conceptual complexity, rapid pacing, or clustered high-stakes assessments. From an administrative and operational standpoint, these courses warrant particular attention. High concentrations of repeat users may contribute to sustained queue pressure and tutor workload, suggesting that targeted interventions such as structured review sessions, supplemental workshops, or coordinated exam preparation programming could alleviate individualized tutoring demand while maintaining academic support quality.

Notably, MATH 2423 and MATH 1823 (i.e., the three-credit hour calculus 1 and 2 courses, respectively, for STEM majors) exhibit the highest percentages of students classified within elevated heavy user categories. This finding indicated that a comparatively large share of students in the calculus sequences engage in tutoring at advanced frequency levels. Given the cumulative and conceptually intensive nature of calculus coursework, sustained engagement with tutoring services in these courses was not unexpected. The data provided evidence that these students were not merely accessing the Math Center episodically but rather incorporating it into their regular academic study routine.

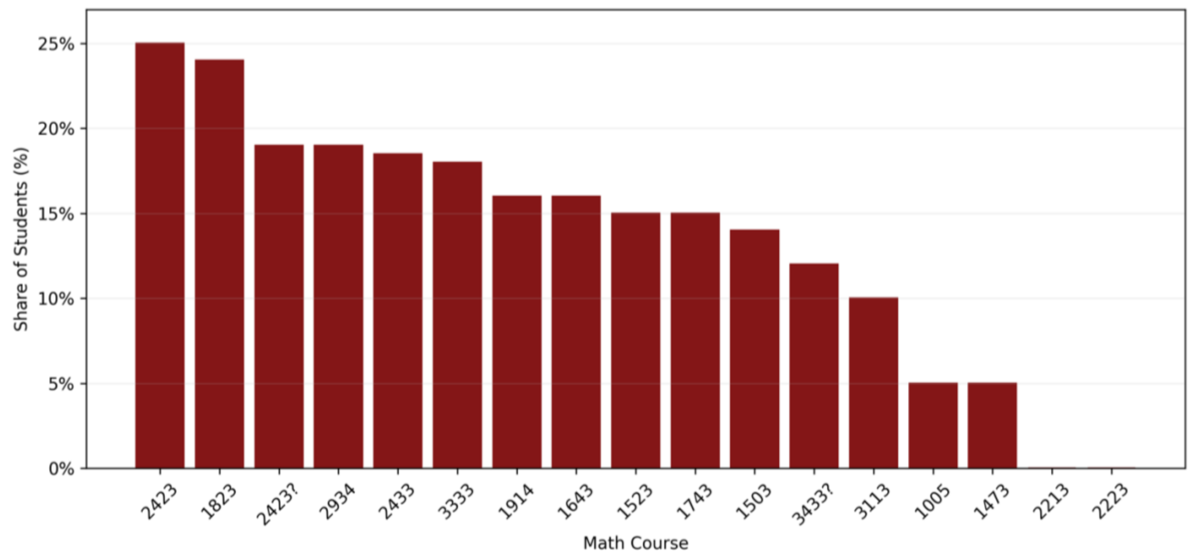
In contrast, MATH 1643 and MATH 1743 (the courses for business, life, and social science majors), while generating substantial overall visitation due to large enrollments, demonstrated relatively lower proportions of heavy users. Students in these courses were accessing tutoring services, but not at the same sustained frequency observed in MATH 1823 and 2423. This distinction is critical. It suggests that math courses for business, life, and social science majors drive demand primarily through breadth of participation (high numbers of unique visitors), whereas the calculus sequence contribute more heavily to intensity of participation (more repeat users and higher heavy user rates).

Taken together, these findings reinforced the importance of distinguishing between volume-driven demand and intensity-driven demand. Courses such as MATH 1643 and MATH 1743 generate high overall traffic due to enrollment scale, while courses such as MATH 1823 and MATH 2423 generate deeper, more sustained engagement among a subset of students. Both dimensions were operationally significant, but they imply different strategies for staffing, resource allocation, and academic intervention.

For figure 5.7 below, we observed the data set looking at what share of students were heavy users.

Figure 5.7

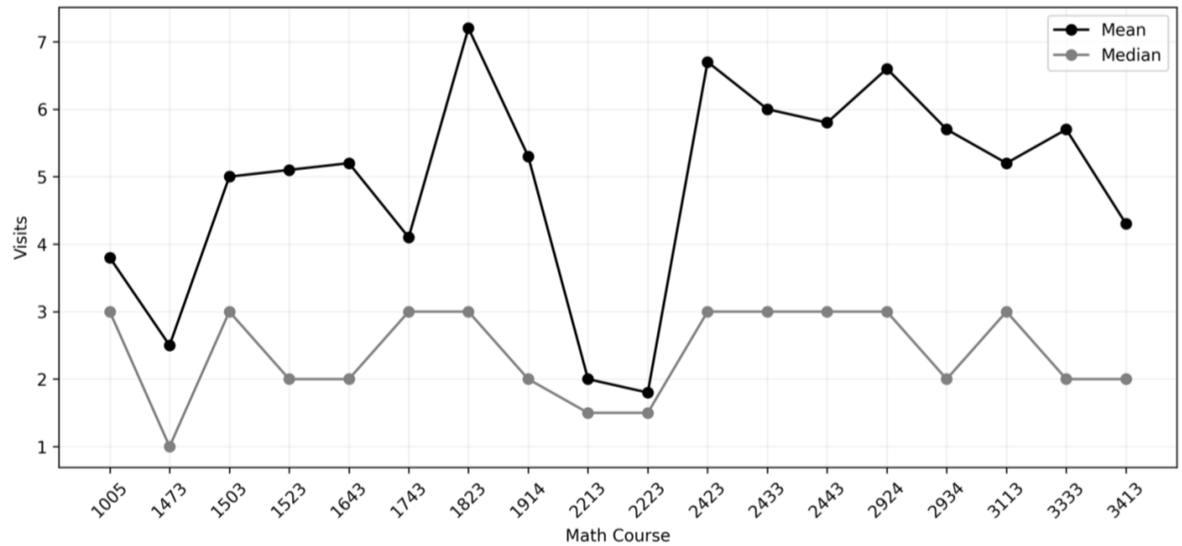
Bar Graph of Heavy Users (those with ten or more visits) Prevalence by Course



To further investigate patterns of participation intensity, we calculated both the mean and median number of visits for each course in the dataset. The comparison between these two measures of central tendency yielded notable and, in some cases, striking results.

Figure 5.8

Line Graph of Mean and Median Visits per Student by Course Over the Entire Dataset



Across many courses, the mean number of visits exceeded the median. This divergence indicated a positively skewed distribution of tutoring participation, wherein a relatively small subset of high-frequency users elevated the average number of visits. In such distributions, the median more accurately reflected the "typical" student experience, while the mean was disproportionately influenced by heavy users. The greater the gap between the mean and median, the stronger the indication that repeat visitation was concentrated among a limited group of students.

This pattern was consistent with earlier findings from the repeat visit bin analysis. The presence of heavy users particularly in courses such as MATH 1823 and MATH 2423 contributed to a right-skewed distribution. While most students attended once or only a few times, a smaller but operationally significant group engages in sustained tutoring participation. These students materially increased total visit counts and, consequently, staffing demand.

The divergence between mean and median underscored the importance of examining distributional structure rather than relying exclusively on aggregate metrics. A course with a moderate mean visitation rate may consist largely of one-time visitors supplemented by a small cluster of intensive users. Without examining both central tendency and distributional shape, such nuances would remain obscured.

From an administrative perspective, this skewness has direct implications for resource planning. Courses characterized by substantial mean-median divergence may benefit from differentiated support strategies. For example, structured group interventions could address recurring conceptual bottlenecks affecting heavy users, while streamlined onboarding or first-visit orientation could improve the experience of single-visit participants.

Ultimately, these findings reinforce a central theme of this study: tutoring demand within the Math Center was multidimensional. Breadth of engagement (unique visitors), intensity of engagement (repeat behavior), proportional engagement (utilization rates), and distributional structure (mean–median divergence) each contributed distinct insight. A comprehensive evaluation of Math Center operations required attention to all these dimensions rather than reliance on any single summary statistic.

Consider the courses separated into bins by course and by room color:

Figure 5.9

100% Distribution Bar graph for Repeat Distribution by Course

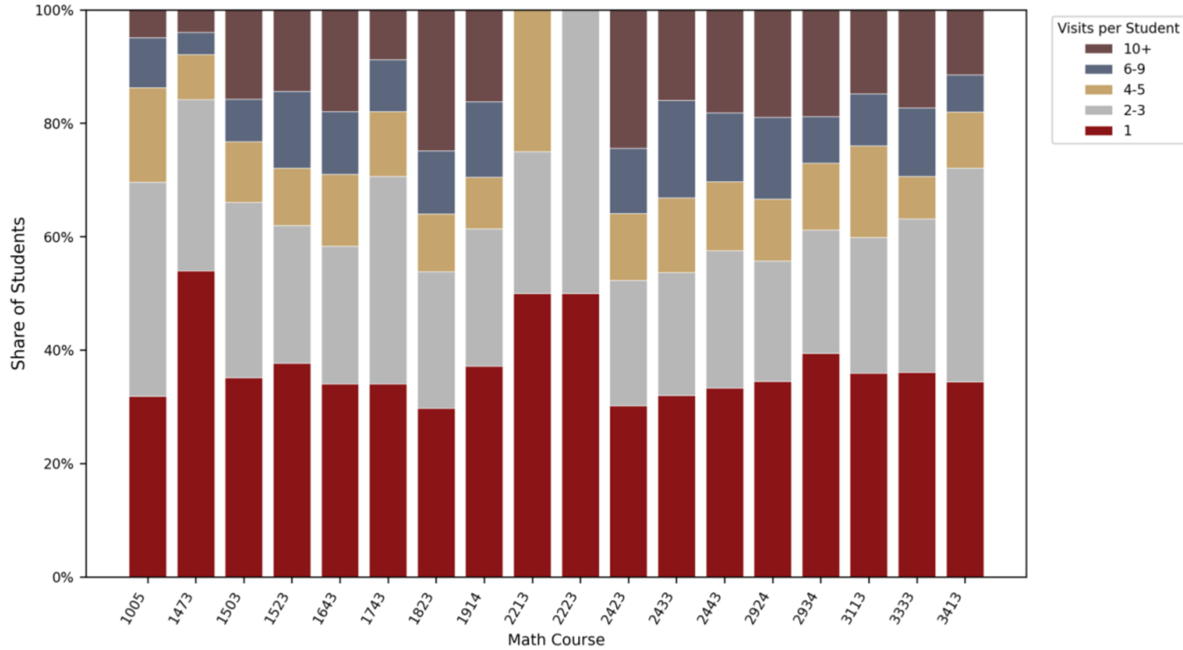


Figure 5.10

100% Distribution Bar graph for Repeat Distribution by Room

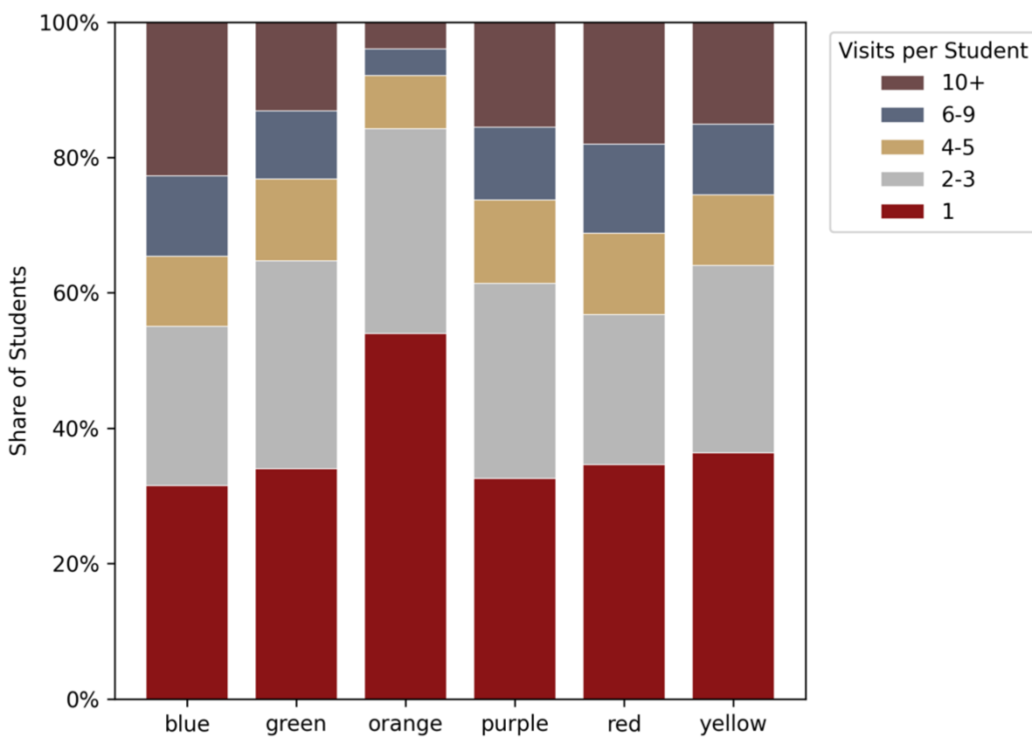


Figure 5.9 disaggregates each course according to the predefined visit-frequency bins of 1, 2–3, 4–5, 6–9, and 10+ visits. Presenting repeat usage at the course-level allowed for a more refined understanding of how participation intensity varied across curricular contexts. While some courses were characterized primarily by single-visit engagement, others displayed a more pronounced right tail, with meaningful proportions of students falling into moderate (4–5 or 6–9 visits) or heavy (10+ visits) usage categories.

Courses with visibly larger 6–9 or 10+ visits segments demonstrated concentrated repeat demand. Such distributions may signal structural academic difficulty, cumulative conceptual layering, clustered assessments, or prerequisite bottlenecks that require sustained support. From an administrative standpoint, identifying courses with elevated repeat density is critical. These courses may benefit from targeted staffing increases during peak assessment windows, structured exam-review programming, or coordinated workshops aimed at mitigating persistent learning barriers.

When repeat usage was aggregated at the room-level, additional structural patterns emerge. Because room color corresponds to clusters of related courses, this aggregation highlighted whether participation intensity was concentrated within curricular strata rather than isolated to individual courses. In this way, room-level analysis provided insight into broader operational patterns across the Math Center.

Rooms exhibiting larger visitation segments (corresponding to 6–9 or 10+ visits) indicated sustained repeat engagement across multiple associated courses. Such patterns may reflect shared characteristics among those courses, including conceptual rigor, common prerequisite pathways, or synchronized assessment schedules. For example, the data provided evidence that courses such as MATH 1473, MATH 2213, and MATH 2223 demonstrate relatively low variance in repeat structure, indicating more stable and moderate engagement patterns without pronounced heavy user concentration.

In contrast, MATH 2423 exhibited the largest concentration of repeat visitors, particularly within the upper frequency bins. This reinforces earlier findings that the MATH 2423 course generates substantial sustained engagement rather than episodic usage. The presence of a thicker heavy-user segment in this course suggests that students may rely on ongoing tutoring support throughout the semester, likely due to the cumulative and conceptually intensive nature of the material.

Collectively, these visualizations reinforced the multidimensional nature of tutoring demand. Course-level repeat structure identified localized intensity patterns, while room-level aggregation revealed broader curricular trends. Both perspectives are essential for informed staffing decisions, resource allocation, and proactive academic intervention planning within the Math Center.

Attendance intensity cannot be fully understood through visit counts alone, as the operational burden of tutoring services is ultimately driven by time expenditure (i.e., duration of visit) rather than only on frequency. Accordingly, this section introduces a time-based analysis by examining both minutes per visit and cumulative minutes per student. This perspective allows for a more direct assessment of resource demand and staffing implications. Time-cost patterns may reflect how students engage with curricular complexity, assessment structures, and conceptual bottlenecks. Longer or repeated sessions may signal heightened academic stakes, cumulative conceptual load, or areas where students encounter persistent difficulty.

Minutes per visit served as an approximation of the time-cost associated with each tutoring interaction. The accompanying boxplots summarize central tendency and dispersion while suppressing extreme outliers (with the baseline dataset excluding sessions exceeding 180 minutes, 12,511 records were removed). By focusing on the distribution rather than isolated maximum values, this visualization provided a clearer representation of typical engagement patterns. Courses with higher median or mean minutes per visit represent more time intensive tutoring interactions and may therefore require greater staffing density or tutors with specialized content expertise.

Figure 5.11 isolated the ten highest volume courses, where operational strain was most consequential. Among these courses, MATH 1823, MATH 1523, MATH 2423, and MATH 2924 exhibited the highest average minutes per visit. However, these courses also demonstrated substantial variance, indicating wide dispersion in session length. Such variability suggests that while many tutoring interactions fall within a typical range, a subset of sessions extended considerably longer, potentially reflecting complex problem-solving tasks or exam preparation demands.

In contrast, MATH 1005 displayed a comparatively lower average session length with minimal variance. This tighter distribution suggested more standardized or contained tutoring interactions, possibly focused on discrete skill reinforcement rather than extended conceptual synthesis.

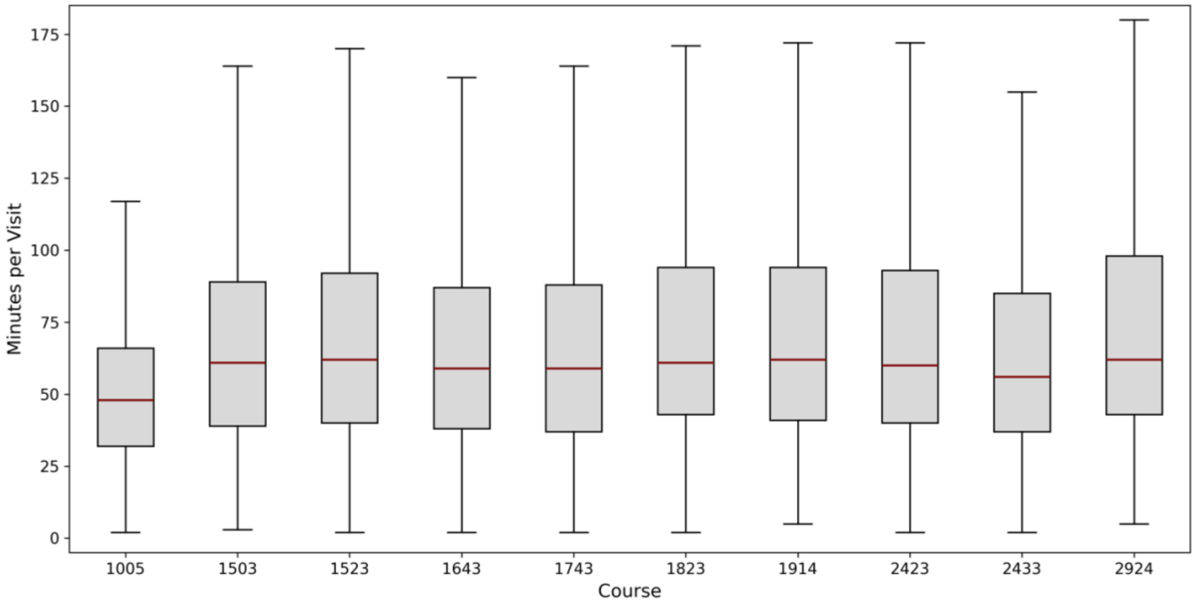
Across most courses, the central tendency (the medians, shown in Figure 5.11) clustered around approximately 50 to 60 minutes per visit, indicating that the typical Math Center session approximated a one-hour engagement. However, Figure 5.11 also reveals meaningful differences in the distribution of session durations across courses. Several courses, particularly MATH 1824, MATH 1914, and MATH 2423, exhibited the widest overall ranges, with upper values extending to approximately 170 to 180 minutes. In addition, these courses demonstrated relatively large interquartile ranges, with the middle 50% of sessions spanning roughly 40 to 90 minutes, indicating substantial variability in typical session lengths. In contrast, MATH 1005 exhibited a noticeably narrower range, with most sessions falling below approximately 120 minutes and a more compact interquartile range, suggesting more consistent and shorter duration visits.

This consistency in median session length provided an important operational benchmark for staffing projections and scheduling models. Nevertheless, the elevated variance observed in several calculus and advanced courses underscored the need for flexible staffing structures capable of accommodating both standard length sessions and more time-intensive engagements. Courses with wider ranges and larger interquartile spreads indicate that student needs are less uniform, requiring tutors to be available for both quick interactions and extended problem-solving sessions. In contrast, courses with tighter distributions suggest more predictable patterns of engagement, which may allow for more stable and efficient staffing allocation.

Taken together, the time-based analysis reinforced the conclusion that tutoring demand must be evaluated not only in terms of frequency but also in terms of duration. Courses with high visit counts and high time variability represented the greatest operational pressure points, whereas courses with lower variability and more consistent session lengths may allow for more predictable staffing allocation.

Figure 5.11

Box Plots of Top 10 Visits Volumes Minutes per Visit



In addition to course-level time intensity, it was important to examine how minutes per visit varied across room assignments. Because rooms correspond to clusters of related courses, room-level time patterns provided an operationally meaningful lens on staffing demand and service structure.

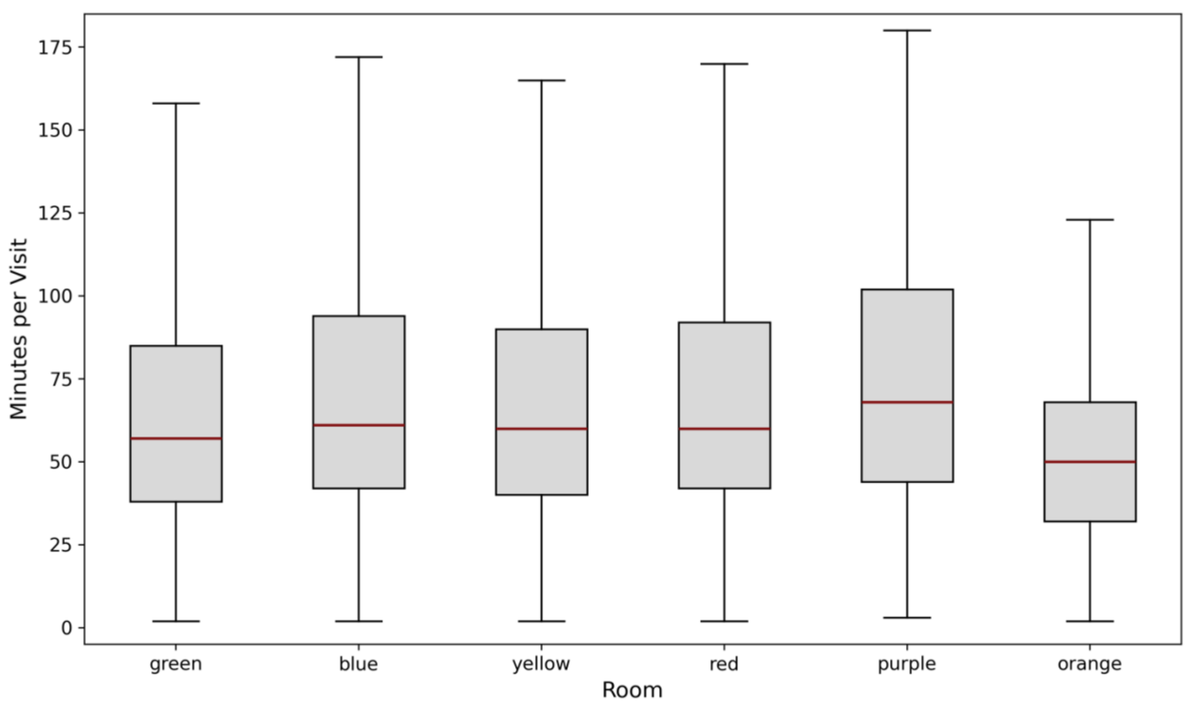
The analysis indicated that the Purple Room exhibited the highest average minutes per visit. So, the tutoring interactions in this room tended to be more time intensive, potentially reflecting the advanced or conceptually dense nature of the courses assigned to that space. Longer average session lengths might indicate cumulative conceptual work, multi-step problem-solving, or sustained exam preparation. From an operational perspective, higher average time per visit increased tutor time cost per student served, which has direct implications for staffing density and scheduling efficiency.

In contrast, the Orange Room demonstrated comparatively shorter average visit durations. This suggests that tutoring interactions within that room may be more targeted or skill specific (as might be expected for an entry-level course), requiring less sustained engagement per session. Shorter session times may allow for higher student throughput per tutor hour, thereby influencing how staffing resources can be allocated most effectively in that space.

Ultimately, incorporating time-based metrics at both the course and room-levels enhanced the operational relevance of the analysis. While visit counts quantify demand volume, minutes per visit more directly captured the resource cost of delivering tutoring services. Together, these measures can enable Math Center administrators to align staffing structures with demonstrated patterns of student engagement and need.

Figure 5.12

Box Plots of Minutes per Visit by Room



The scatterplot below shows the relation between two central dimensions of tutoring intensity: repeat engagement (mean visits per student) and per-visit time cost (mean minutes per visit). By combining both measures, the visualization provides a multidimensional representation of operational demand. Courses positioned in the upper-right quadrant, those characterized by both higher average visit frequency and longer average session duration, represent the greatest workload pressure on the Math Center. These courses generated demand not only through repeated student engagement but also through sustained time investment per interaction.

The inclusion of course labels enhance the administrative utility of the figure. By identifying courses occupying high intensity regions of the plot, Math Center leadership can strategically target interventions. For example, courses that demonstrated elevated repeat frequency and extended session times may benefit from structured group review sessions, expanded staffing during peak assessment periods, or course-specific tutor training designed to address recurrent conceptual bottlenecks. Such targeted measures may improve instructional efficiency while maintaining service quality.

Operationally, this integrated intensity framework complements earlier repeat usage and time distribution analyses by simultaneously positioning courses along two dimensions: average visit frequency and average session duration. Figure 5.13 is divided into four quadrants using the overall mean values as reference lines. The upper-right quadrant represents high-frequency, long-duration courses, which place the greatest sustained demand on tutoring resources. These courses require both repeated engagement and extended tutoring time, making them primary targets for increased staffing density and specialized tutor allocation.

The upper-left quadrant captures low-frequency, long-duration courses, where students attend less often but require substantial time when they do. These patterns suggest more episodic but intensive support needs, potentially reflecting complex or higher-level material that demands deeper, less frequent intervention. The lower-right quadrant includes high-frequency, short-duration courses, which indicate repeated but more transactional usage patterns. These courses may benefit from streamlined support structures, such as quick-check assistance or high-throughput tutoring models. Finally, the lower-left quadrant represents low-frequency, short-duration courses, which exert the least operational pressure and may require minimal targeted staffing beyond baseline coverage.

Importantly, each course is color-coded according to its associated room band, with the color of each point corresponding to the primary room in which tutoring for that course occurs. This allowed for simultaneous interpretation of both service intensity and spatial organization within the Math Center. Clustering of similarly colored points within quadrants highlights how certain room bands systematically concentrate higher or lower intensity courses, reinforcing the connection between curricular structure and spatial resource allocation.

The service intensity scatterplot revealed clear distinctions in how courses utilized the Math Center across both visit frequency and session duration. When figure 5.13 was divided into quadrants using the overall mean values, distinct patterns emerged that aligned closely with both course-level and room bands.

The upper-right quadrant, representing high-frequency and long-duration engagement, contained a substantial concentration of courses from the purple, red, and blue room bands. Specifically, two of the three purple room courses, most red room courses, and all blue room courses were in this region, along with Pre-calculus from the yellow room. This clustering indicated that these courses simultaneously generated repeated visits and extended session durations, placing the greatest sustained demand on tutoring resources. These patterns suggested that students in these courses not only returned frequently but also required prolonged engagement during each visit, consistent with more conceptually dense or cumulative material. Notably, the calculus courses applied the heaviest strain on the Math Center.

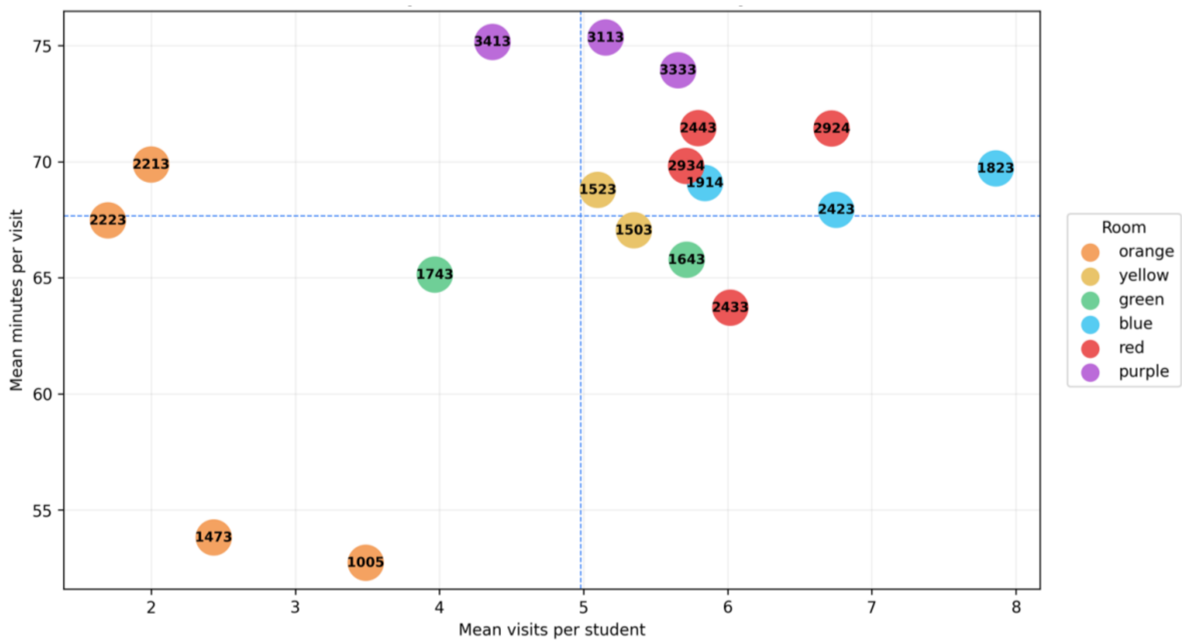
The upper-left quadrant, defined by lower visit frequency but longer session duration, included the remaining purple room course, Physical Mathematics as well as two courses from the orange room band. This pattern suggested that students in these courses attended less frequently, but when they did, required substantial time to work through material. This type of engagement reflected episodic but intensive support needs, likely associated with courses that demand deeper problem-solving or extended conceptual explanation during each visit.

The lower-left quadrant, representing low-frequency and short-duration engagement, was notably anchored by MATH 1743, the course with the highest number of unique visitors overall, along with two additional orange room courses. Despite its high overall participation, MATH 1743 exhibited relatively shorter and less frequent per-student engagement. This indicated that while many students accessed the Math Center for this course, their visits tended to be brief and less repeated, reflecting a high-throughput usage pattern rather than sustained individual demand.

The lower-right quadrant, characterized by higher visit frequency but shorter session duration, included MATH 1643, the other large-enrollment gateway course from the green room, along with one course from the red room band. This pattern suggested consistent and repeated use of tutoring services, but with shorter, more targeted sessions. Such behavior aligned with structured, coordinated courses where students frequently sought clarification or reinforcement rather than extended instruction.

Figure 5.13

Scatter Plot of Service Intensity by Course



To extend beyond descriptive analysis, we implemented a modeling framework designed to quantify how tutoring demand varied by course after accounting for differences in enrollment size. Visit counts were aggregated at the course–semester level and modeled using a generalized linear modeling approach that included the logarithm of course enrollment as an exposure offset. Incorporating log(enrollment) as an offset standardized visit counts by the number of students enrolled in each course, allowing the model to estimate expected visits per enrolled student rather than total visits. This adjustment ensured that comparisons across courses were not driven simply by differences in class size, but instead reflected differences in proportional utilization.

This allowed visit counts to be interpreted as rates rather than raw totals. In practical terms, the model estimated how frequently an average student in a given course used the Math Center, enabling direct comparison across courses with substantially different enrollments.

Without this adjustment, high-enrollment gateway courses would dominate purely due to scale, obscuring courses that generated disproportionately high demand relative to their size.

Model results were expressed as exponentiated coefficients, or incidence rate ratios (IRRs), which represent multiplicative differences in expected visit rates relative to a designated reference course. The Poisson regression model served as an initial baseline for modeling count outcomes. However, it assumes equidispersion, meaning that the mean and variance of the outcome are equal. This assumption was not consistent with the observed data, as tutoring participation exhibited clustering and heavy-tailed behavior, with some students engaging far more frequently than others.

To assess this formally, we evaluated the dispersion ratio, defined as the Pearson Chi-square statistic divided by its degrees of freedom. The resulting value of 45.74 substantially exceeded 1, indicating significant overdispersion and confirming that the Poisson model would underestimate variability and overstate statistical precision. Consequently, the Negative Binomial model was adopted, as it relaxes the equidispersion assumption by allowing the variance to exceed the mean. This specification provided more reliable standard errors and more appropriate inferential conclusions for the observed data structure.

Figure 5.14 presents course-level effects derived from the Negative Binomial model, reported as incidence rate ratios (IRRs) relative to MATH 1643, which was selected as the reference course due to its role as a large-enrollment, high-usage gateway course that provided a stable and interpretable baseline for comparison. An IRR greater than 1 indicated that, after controlling for enrollment, a course generated a higher expected visit rate per student than MATH 1643, while an IRR below 1 indicated lower proportional demand. These estimates provided a direct measure of disproportionate tutoring utilization, distinguishing courses that generated elevated demand relative to their size from those whose usage aligned more closely with enrollment.

Figure 5.15 displays semester-level effects from the same Negative Binomial framework. These estimates indicated whether overall tutoring utilization intensity differed across semesters after controlling for both course composition and enrollment exposure. Observed semester-level variation may reflect broader institutional or structural factors, including cohort differences, changes in course coordination, shifts in assessment timing, or variation in student preparedness. Interpreting these semester effects alongside course-level IRRs allowed for differentiation between course-specific demand patterns and broader systemic trends.

Figure 5.14

Line Graph of Negative Binomial Course Effects

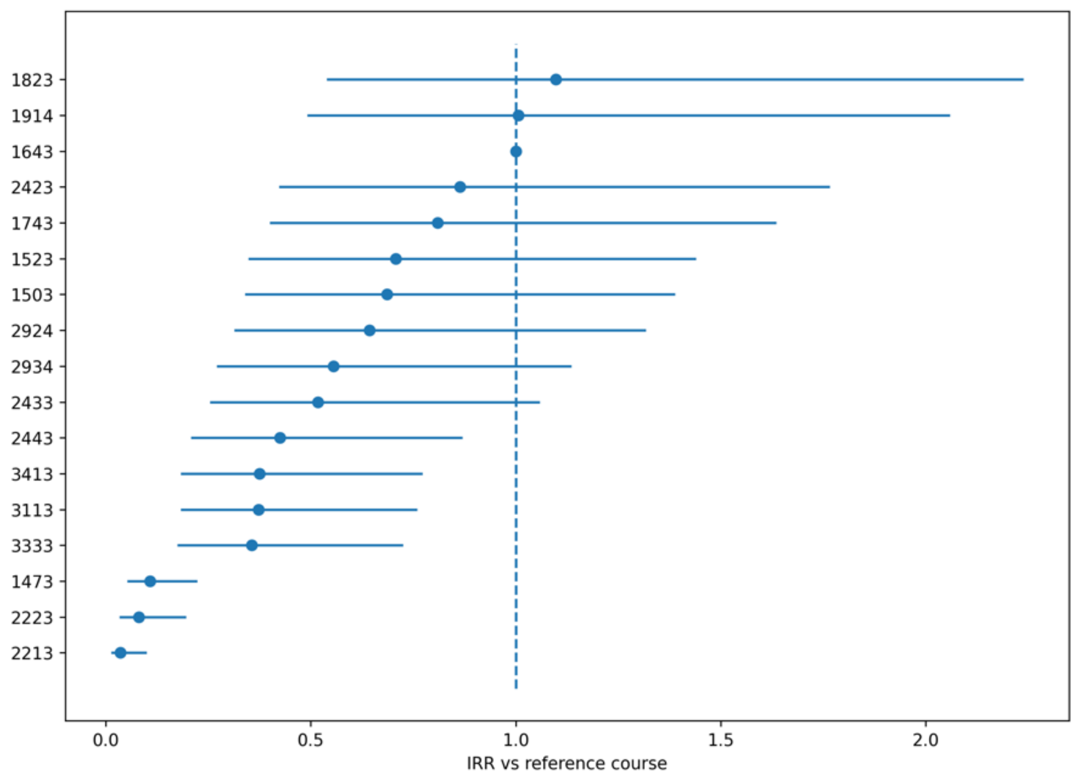
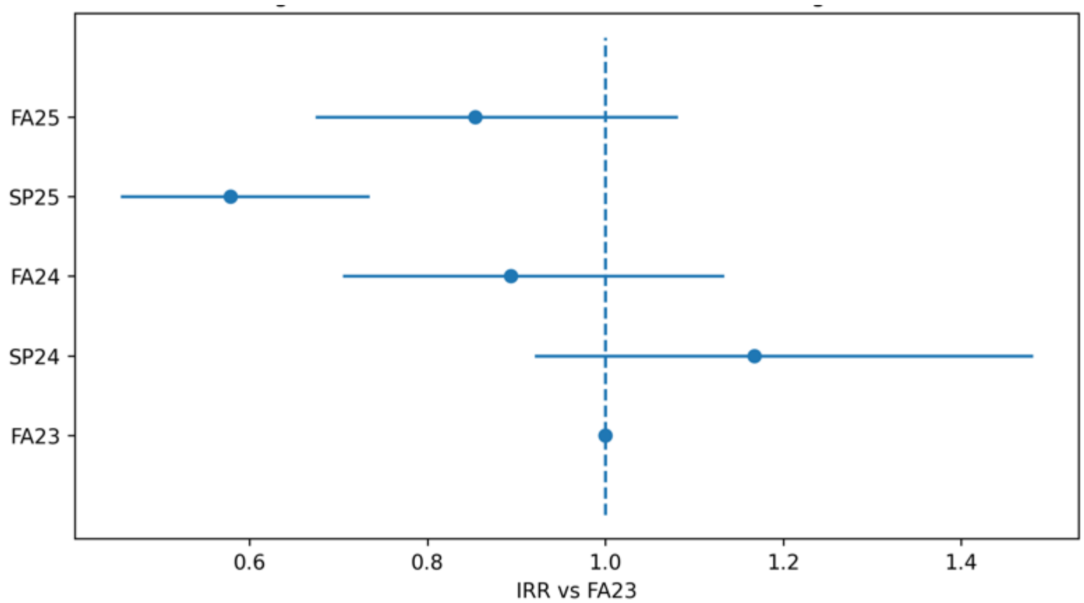


Figure 5.15

Line Graph of Negative Binomial Semester Effects



Courses with the largest IRRs represented the highest levels of enrollment-adjusted demand per student. In practical terms, students in these courses utilized the MLC at disproportionately higher rates than those in the reference course, even after controlling for differences in class size. This pattern suggested sustained and repeated help-seeking behavior, indicating that students in these courses returned multiple times for support rather than resolving difficulties in a single visit.

From an operational perspective, elevated IRRs therefore signaled courses where demand was both frequent and persistent at the individual student level. Because repeated visits reflect ongoing difficulty rather than isolated need, these courses placed sustained pressure on tutoring resources and were natural priorities for staffing allocation, particularly during peak assessment periods.

These patterns aligned with prior research on mathematics tutoring centers, which has emphasized that student engagement in these environments is often structured around recurring help-seeking behaviors rather than one-time use (Byerley et al., 2020). Work by Mills, Byerley, and colleagues has highlighted that effective tutoring centers must align organizational structures, tutor preparation, and service models with the types of interactions and learning needs that repeatedly emerge across courses (Byerley et al., 2023; Mills et al., 2020). Additionally, research on tutor practices has shown that tutoring interactions often follow recurring behavioral patterns that can be anticipated and improved through targeted preparation (Johns et al., 2022).

Courses with high IRRs may benefit from targeted interventions that address recurring conceptual challenges more systematically. Aligning tutor preparation with known areas of difficulty can improve responsiveness during sessions, while structured review opportunities may reduce the need for repeated individual visits by addressing common bottlenecks more efficiently.

Elevated enrollment-adjusted demands serve as signals of curricular locations where students were consistently seeking external tutoring support to navigate course expectations. When students repeatedly mobilize tutoring resources to succeed, these courses should be examined to see how course design, assessment structure, and support systems interact.

Thus, courses with high IRRs are not merely operational pressure points, but they also represent meaningful contexts for studying the relationship between institutional support structures and student persistence in mathematics. Identifying these areas could enable both more efficient administrative planning and more focused inquiry into how academic support can be strategically aligned with curricular design to improve student outcomes.

Research Question 1 asked: *What is the overall attendance of the Math Center, and how is that attendance distributed across different mathematics courses?*

The analyses presented in this section demonstrated that tutoring demand within the Math Center was both substantial and structurally differentiated across the undergraduate mathematics curriculum. Attendance was not uniformly distributed; rather, it reflected distinct patterns of breadth, intensity, proportional engagement, and time cost burden across courses and semesters.

First, high-enrollment gateway courses, most notably MATH 1743 and MATH 1643, drove overall attendance volume. These courses accounted for the largest numbers of unique visitors and total visits, confirming that enrollment scale was a primary contributor to aggregate demand. Structural changes, such as the integration of MATH 1005 into the mathematics department and coordination changes in MATH 1743, corresponded with measurable increases in visitation, indicating that curricular and administrative decisions can substantially influence tutoring utilization.

Second, enrollment-normalized utilization rates revealed that raw visit counts alone do not fully explain demand. After adjusting for enrollment, certain courses, particularly gateway and early sequence calculus courses, demonstrated disproportionately high engagement. Fall semesters consistently exhibited higher utilization rates than Spring terms, suggesting systematic variation in help-seeking behavior across the academic calendar.

Third, repeat usage analyses highlighted that tutoring demand was layered rather than evenly distributed. While the largest share of students attended the Math Center only once within a semester, accounting for roughly one-third of all users, the first and second three-credit calculus courses, namely MATH 1823 and MATH 2423, exhibited the highest concentrations of heavy users, indicating that these courses generated intensity-driven demand.

Fourth, incorporating time-based metrics revealed that operational burden was shaped not only by visit frequency but also by session duration. Across most courses, typical visits clustered around 50–60 minutes. However, several calculus and upper-division courses exhibited both higher average minutes per visit and greater variance. The Purple Room demonstrated elevated average session lengths, indicating concentrated time-cost intensity. When repeat frequency and session duration were integrated into a single intensity framework, certain courses emerged as high-pressure nodes combining frequent attendance with prolonged engagement, thereby exerting the greatest strain on staffing resources.

Finally, rate-adjusted modeling using a Negative Binomial framework confirmed that differences in demand persist even after accounting for enrollment exposure. The substantial overdispersion detected in the Poisson model justified the use of the Negative Binomial specification. Course-level incidence rate ratios identified which courses generated disproportionately high visit rates per enrolled student, providing a statistically grounded prioritization tool for staffing allocation and proactive intervention. Semester effects further contextualized demand shifts across terms, suggesting that institutional and cohort-level dynamics also influenced utilization intensity.

Taken together, the findings for the first research question established that MLC attendance is multidimensional. Demand varied across courses in terms of breadth (unique visitors), volume (total visits), proportional engagement (utilization rates), intensity (repeat behavior), time cost (minutes per visit), and enrollment-adjusted rates (IRRs). Gateway courses dominated overall volume, calculus sequences drove sustained repeat intensity, and advanced courses exhibited more variable proportional engagement. These layered patterns provide both operational guidance for administrators and a foundation for deeper investigation into how curricular structure and institutional supports shape student help-seeking behavior.

With a comprehensive understanding of overall attendance and its distribution now established, the analysis proceeds to the second research question.

Attendance Patterns Data over the Academic Year

The second research question guiding this analysis is:

> *What are the patterns of student attendance at the Math Center, and how do these patterns vary depending on the time of the academic year and the specific mathematics course?*

While the first research question focused on overall volume and proportional demand, the second is focused on temporal structure. The goal of this section is to identify when tutoring demand occurs, how it fluctuates throughout the semester, and whether those fluctuations differ systematically by course. Understanding timing patterns is operationally critical, as staffing decisions, space utilization, and service accessibility depend not only on how much demand exists, but when that demand materializes.

To address the second research question comprehensively, several sub-questions were developed, each targeting a distinct temporal dimension of attendance.

First, we examined peak days of the week for student attendance at the Math Center. This analysis identified whether demand clusters on specific weekdays and evaluated the extent to which peak day patterns vary across courses. Certain courses may generate mid-week concentration tied to lecture pacing or assignment due dates, while others may show more distributed patterns.

Second, we analyzed peak hours of attendance within each day. This dimension assessed the day concentration of demand and evaluated how peak-hour intensity varies by both day of the week and specific course. Identifying peak hours is particularly relevant for staffing allocation considerations, as even modest shifts in concentration can substantially alter queue dynamics and tutor workload.

Third, we investigated the relationship between attendance spikes and coordinated exam schedules. For courses with synchronized assessments, particularly gateway and calculus sequences, exam timing were thought of as possible candidates to generate predictable surges in tutoring demand. By aligning attendance data with exam calendars, we assessed whether peaks corresponded with assessment events and whether the magnitude of those peaks differed by course.

Fourth, we examined peak weeks throughout the semester. This longitudinal analysis identified whether attendance followed recurring semester-wide rhythms and whether these peak weeks varied significantly across different mathematics courses. We were cognizant that courses with cumulative conceptual structures might exhibit increases over time, while other courses might show sharp, short-lived spikes aligned with specific assessment windows.

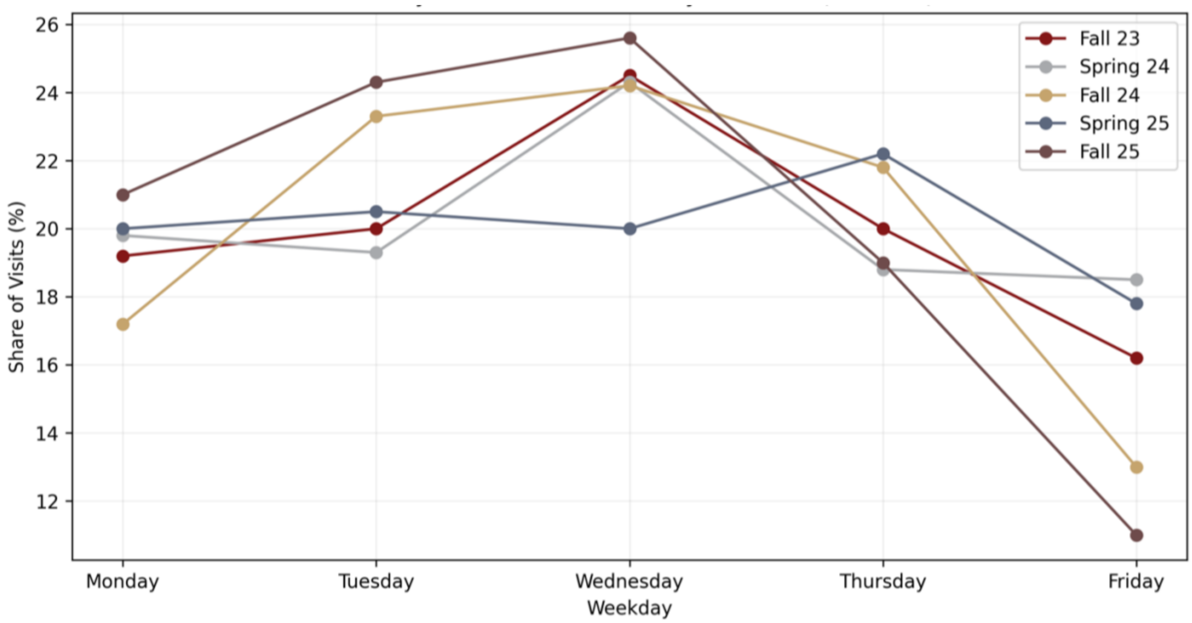
Collectively, these sub-questions position this section as a focused analysis of attendance patterns rather than attendance volume. The emphasis of this section then is on identifying cyclical behavior, clustering effects, and course-specific temporal signatures. By modeling daily, hourly, and weekly variation, this section should provide a structured understanding of how tutoring demand unfolds over the academic calendar.

Such pattern-based analysis is essential for operational forecasting and proactive planning. Rather than responding reactively to attendance surges, identifying predictable temporal rhythms should enable the Math Center administration to align staffing density, tutor expertise, and programming efforts with empirically observed demand cycles.

We now turn to the weekday distribution of visits over each of the semesters in our data set.

Figure 5.16

Line Graph of Weekday Distribution of Visits by Semester



Analysis of weekday attendance patterns revealed a consistent concentration of visits midweek. Across all semesters except Spring 2025, Wednesdays accounted for the highest percentage of total Math Center visits, followed closely by Tuesdays. This pattern suggested that tutoring demand built early in the week and peaked at its midpoint. Mondays and Thursdays exhibited moderate and relatively comparable levels of activity, serving as transitional days between the early-week buildup and the late-week decline.

In contrast, Fridays consistently represented the lowest visitation day across semesters. This decline was likely influenced not only by reduced course scheduling, student travel patterns, or shifting academic priorities, but also by the fact that the Math Center operated with reduced hours on Fridays. This structural constraint likely contributed to the observed decrease in visits and should be considered when interpreting differences across weekdays.

This weekday imbalance had direct staffing implications. Concentrated midweek demand would have required higher tutor density and potentially expanded service coverage from Tuesday through Wednesday when visitation peaked. Mondays and Thursdays, which exhibited similar but slightly lower levels of demand, may have required moderate staffing levels that balanced coverage with efficiency. In contrast, Fridays may have supported leaner staffing models or alternative programming structures due to both reduced demand and limited operating hours.

Importantly, the persistence of this weekday pattern across multiple semesters suggested structural regularity rather than isolated anomalies. The consistency of midweek peaks and Friday troughs indicated that attendance timing was closely aligned with the academic rhythm of the institution. Understanding these predictable temporal dynamics should enable Math Center administration to align staffing resources with demonstrated patterns of student help-seeking behavior, thereby improving both service efficiency and responsiveness.

The hourly distribution of student logins provided additional insight into within-day demand patterns. As shown in the figure below, peak sign-ins occurred around 10:00 a.m. and 1:00 p.m. These time blocks represented the highest concentration of student arrivals at the Math Center and therefore marked the most acute intake pressure periods within the daily service cycle.

Several structural explanations likely contributed to these peaks. Late morning and early afternoon hours often aligned with gaps between scheduled classes and common lunch periods, making these windows convenient for students seeking tutoring support. Additionally, these times frequently preceded afternoon lectures or lab sessions, prompting students to seek clarification before returning to class. The dual-peak pattern indicated that demand was not evenly distributed throughout the day but instead clustered around transitional academic periods.

This pattern reflected fundamental principles of service demand concentration. When arrivals clustered in predictable windows, queue formation and service congestion became primary operational concerns. Because tutoring was both time-intensive and cognitively demanding, arrival surges during peak hours could quickly strain staffing capacity if not proactively managed. Even when total daily volume remained stable, uneven hourly distribution increased workload variability and reduced service efficiency.

Moreover, the existence of distinct arrival peaks reinforced the importance of aligning staffing schedules with empirically observed demand rather than relying on evenly distributed tutor coverage throughout the day. Concentrated sign-in periods may have warranted increased tutor density, staggered shift transitions, or structured intake management during those windows. Conversely, off-peak hours may have allowed for targeted programming, administrative tasks, or professional development activities without compromising service availability.

In sum, the 10:00 a.m. and 1:00 p.m. peaks demonstrated that Math Center utilization followed predictable daily rhythms shaped by class schedules and student academic behavior. Recognizing and planning for these demand clusters could strengthen operational efficiency and ensure that staffing resources were deployed where and when they were most needed.

Figure 5.17

Line Graph of Check-In Hour Profile by Semester

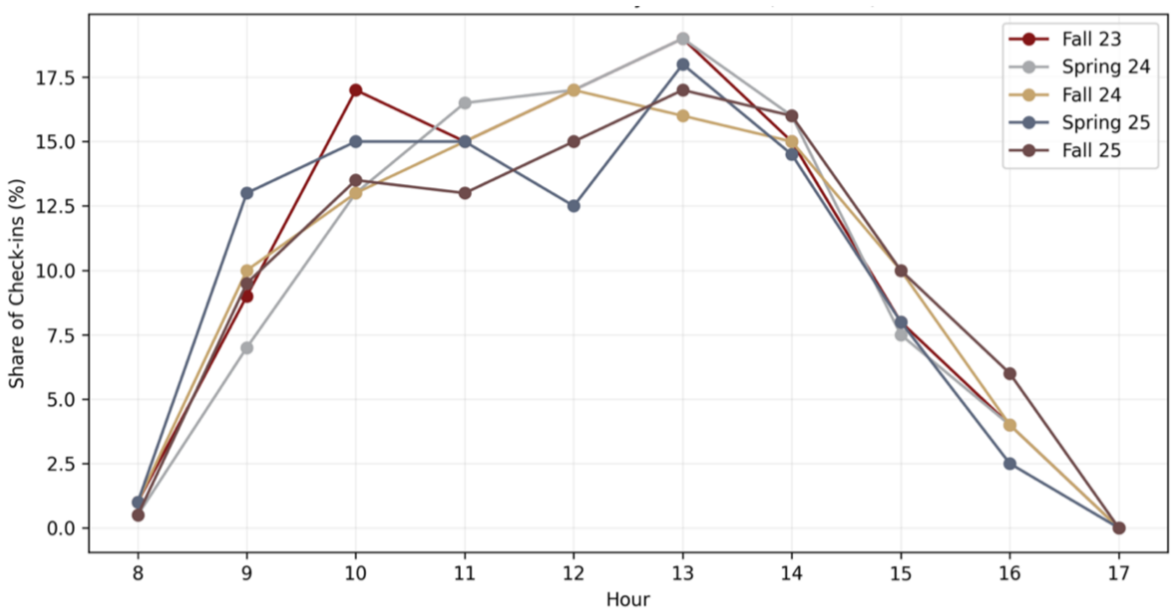
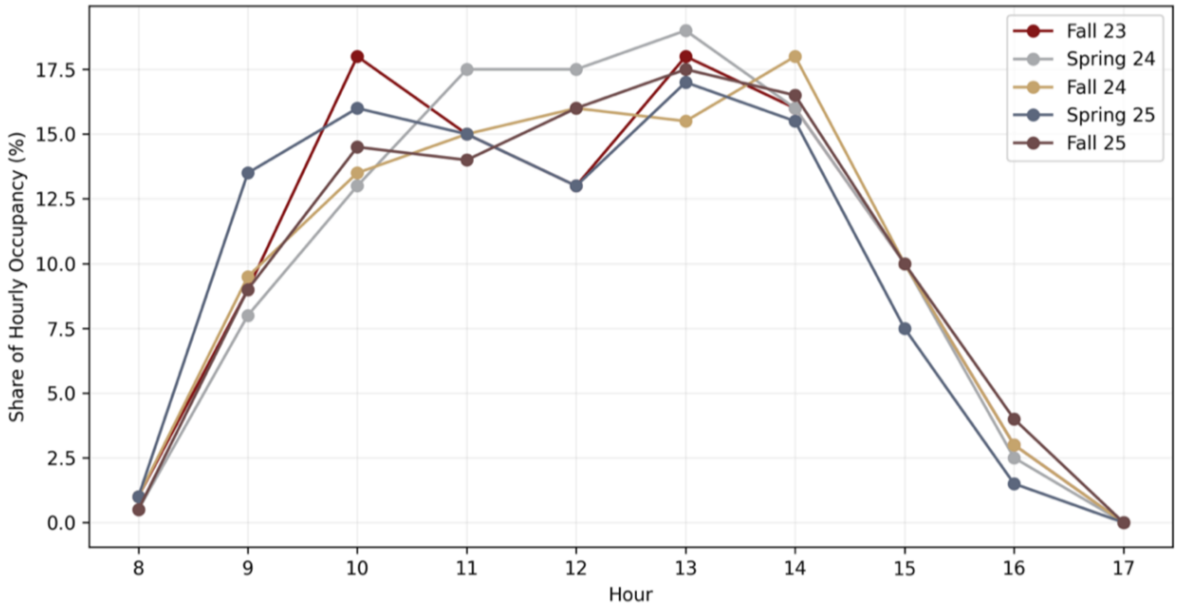


Figure 5.18 presents the hourly occupancy profile of the Math Center across five semesters, illustrating the percentage share of daily traffic occurring during each operating hour. Several consistent structural patterns can be taken from this visualization.

Figure 5.18

Line Graph of Hourly Occupancy Profile by Semester



First, demand built steadily from opening through late morning, with a pronounced surge between 9:00 a.m. and 10:00 a.m. Across semesters, the 10:00 a.m. hour represented one of the first major inflection points in occupancy. This confirmed earlier sign-in analyses indicating late morning as a high arrival window. The steep increase from 8:00 a.m. to 10:00 a.m. suggests that students rarely arrive immediately at opening but instead cluster after their first scheduled class or during mid-morning academic transitions.

Second, the data show a sustained plateau from approximately 11:00 a.m. through 2:00 p.m., with the overall peak consistently occurring around 1:00 p.m. In Fall 2023, for example, 1:00 p.m. approached 20% of total daily occupancy, the highest hourly concentration observed across semesters. Other semesters demonstrated a similar pattern, with 1:00 p.m. or 2:00 p.m. serving as the dominant hour. This mid-day concentration indicates that the Math Center typically experiences its greatest sustained workload during the late morning to early afternoon window.

Third, after 2:00 p.m., occupancy declined steadily across all semesters. By 3:00 p.m., hourly share drops substantially, and by 4:00 p.m., traffic became comparatively light. The final operating hour consistently showed negligible occupancy. This tapering pattern suggested that demand is front loaded within the academic day, with relatively limited late-afternoon utilization.

Importantly, while minor semester-to-semester variation existed in the precise magnitude of peak hours, the overall shape of the curve remained highly stable. Each semester exhibited a low early morning baseline, a sharp rise through mid-morning, a broad mid-day plateau with a peak near 1:00 p.m., and a steady afternoon decline.

This consistency suggests that hourly demand patterns are structurally embedded in the institutional schedule rather than driven by semester-specific anomalies. Class scheduling blocks, common break times, and coordinated exam windows likely shape these rhythms.

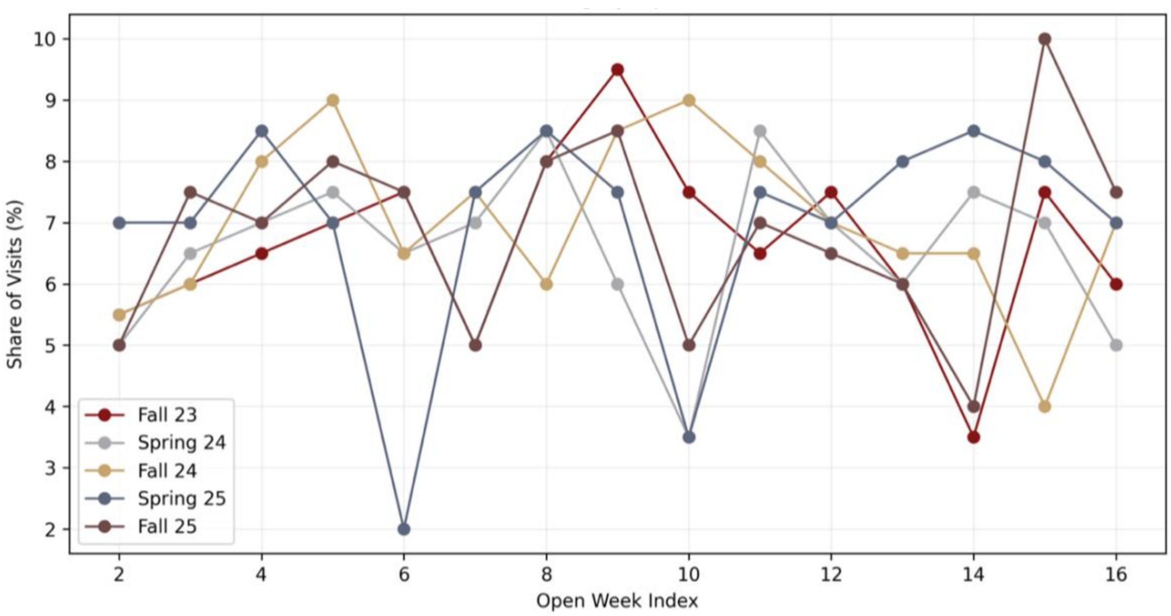
The stability of this hourly profile has direct staffing implications. Tutor density should be maximized between 10:00 a.m. and 2:00 p.m., particularly around 1:00 p.m., when both arrival pressure and occupancy were highest. Conversely, early morning and late afternoon hours might allow for reduced staffing levels or alternative programming structures without significantly compromising service access.

More broadly, the figure reinforced a key finding of this study that tutoring demand is not only multidimensional across courses but also temporally patterned within each academic day. Recognizing and planning for these predictable occupancy rhythms could enable more efficient alignment of staffing resources with empirically observed student behavior.

Figure 5.19 displays the semester distribution of visits by open week (the weeks of the semester the Math Center is open) across five semesters. Unlike the hourly profile, which exhibited strong structural stability, the weekly distribution, as shown in the figure, reveals a cyclical pattern characterized by recurring peaks and troughs throughout the term.

Figure 5.19

Line Graph of Open Week Share of Visits



Several broad trends are immediately apparent. First, attendance did not steadily increase or decrease across the semester; rather, it fluctuated in waves. Most semesters exhibited elevated visitation in Weeks 4–5, again around Weeks 8–9, and in Weeks 13–15. These clusters aligned closely with typical assessment cycles in undergraduate mathematics courses, particularly coordinated midterms, and pre-final review periods.

Second, sharp declines in attendance appeared in specific weeks across multiple semesters. For example, Week 10 consistently shows one of the lowest shares of visits in several terms. Similarly, isolated troughs appear around Week 14 in certain semesters. These dips correspond to institutional calendar effects such as fall or spring breaks, campus holidays, or natural pauses between major assessment events. The magnitude of these troughs reinforced the sensitivity of tutoring demand to broader academic scheduling structures.

Third, while the shape of the semester pattern was similar across terms the magnitude of the peaks varied. For instance, Fall 2023 shows a pronounced spike around Week 9, whereas Fall 2025 demonstrated a substantial surge in Week 15. These differences suggested that while general assessment rhythms shape demand, the exact timing and intensity of spikes may depend on course coordination schedules, exam clustering, or cohort specific factors.

Importantly, the recurrence of multi-peak cycles supported the interpretation that tutoring demand is closely linked to assessment preparation. Rather than reflecting generalized background support usage, visitation surges appear strategically timed around high stakes academic events. This pattern aligns with research on help-seeking behavior, which consistently finds that students are more likely to mobilize academic resources in response to perceived evaluative pressure.

The weekly oscillation pattern has direct staffing implications. Rather than allocating uniform tutor coverage across the semester, administrators may benefit from dynamic staffing models that scale capacity during predictable high demand weeks. Conversely, lower demand weeks may allow for professional development, targeted outreach, or structured programming without compromising service accessibility.

In sum, the weekly timing analysis revealed that Math Center attendance followed a patterned, assessment-driven rhythm across semesters. Demand concentrated around recurring academic milestones rather than increasing monotonically over time. Recognizing these cyclical peaks enhances both forecasting accuracy and the strategic deployment of tutoring resources throughout the semester.

To further refine the temporal analysis, we now turn to attendance patterns by room, examining both peak days of the week and peak check-in hours within each space. Because rooms correspond to clusters of related courses, this analysis allows us to determine whether temporal demand patterns differed across curricular strata. Note, the Orange Room was included in this portion of the analysis, however its significance in the dataset is largely concentrated in Fall 2025 following the inclusion of MATH 1005.

Blue Room Weekly Visitation Profile

The Blue Room (which houses 1823, 1914 and 2423, refer to Table 4.2 for course names) experienced its highest visitation on Mondays, Wednesdays, and Fridays. This pattern contrasted with the broader Math Center trend, with Wednesdays having higher overall attendance and Fridays having lower overall attendance generally. The Blue Room's relative Friday strength suggested that the courses assigned to this space may structure assignments or assessments in ways that generate end of week support needs. Hourly check-in data indicated that demand is concentrated between 10:00 a.m. and 2:00 p.m., aligning with the institution wide mid-day peak. This sustained four-hour window represents the primary operational pressure period for this room.

Figure 5.20

Line Graph of Blue Room Peak Days

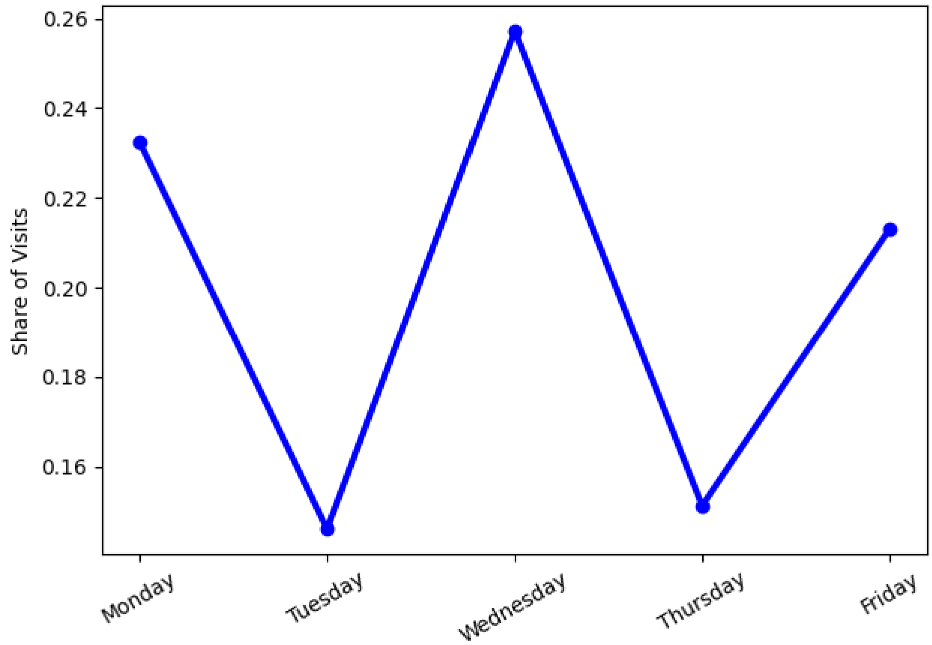
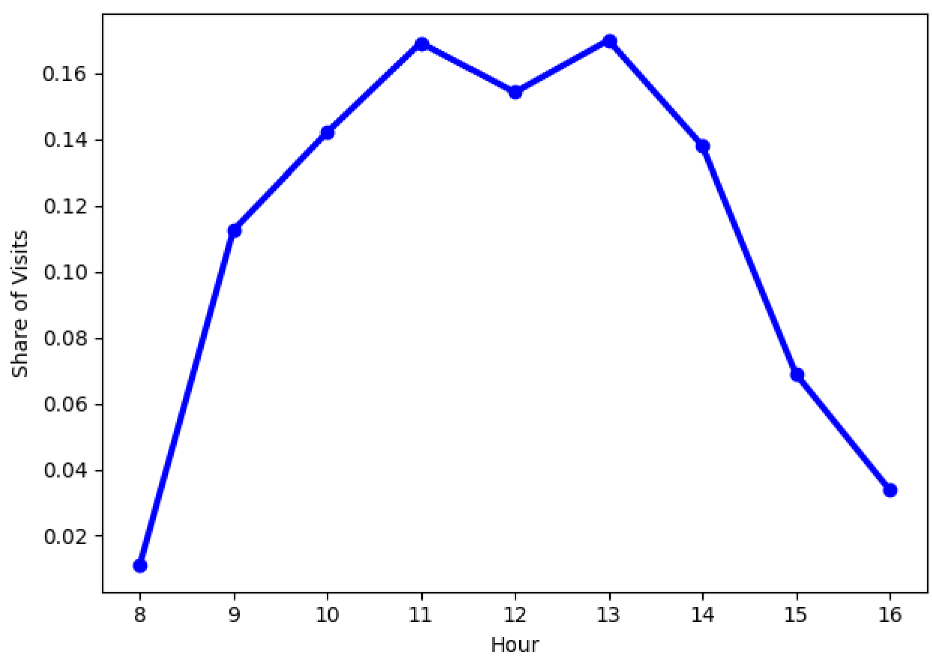


Figure 5.21

Line Graph of Blue Room Peak Check-In Hour



Green Room Weekly Visitation Profile

The Green Room exhibited its strongest attendance on Tuesdays and Thursdays, with a noticeable dip on Wednesdays. This alternating day concentration likely reflects the lecture cadence of the larger MATH 1743 courses, which often have Tuesday/Thursday meeting times, assigned to this room. Hourly patterns show peak check-ins between 12:00 p.m. and 2:00 p.m., with the most pronounced spike at 1:00 p.m. This sharper mid-day surge suggested more concentrated arrival behavior compared to the broader plateau observed at the center-wide level.

Figure 5.22

Line Graph of Green Room Peak Days

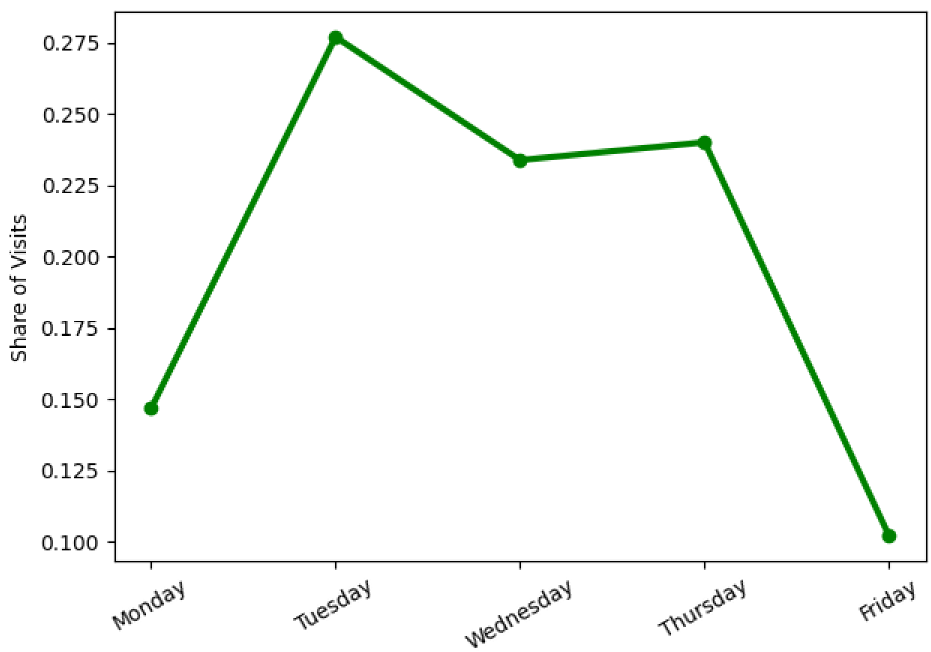
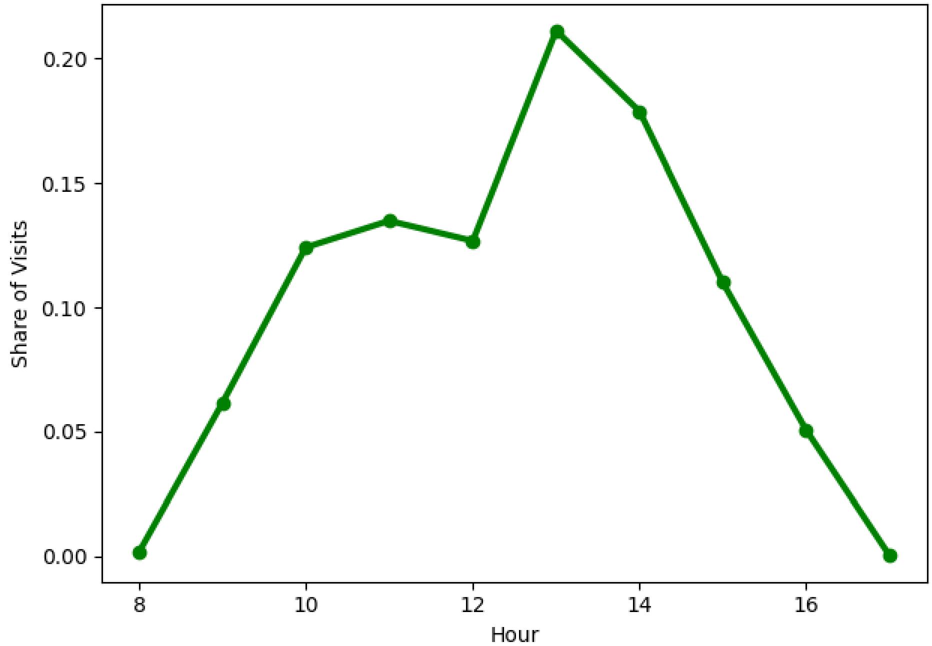


Figure 5.23

Line Graph of Green Room Peak Check-In Hour



Purple Room Weekly Visitation Profile

The Purple Room also demonstrated elevated visitation on Tuesdays and Thursdays. However, its hourly concentration differed slightly from the Green Room. Check-ins were highest between 10:00 a.m. and 12:00 p.m., with a pronounced spike at 11:00 a.m. This earlier mid-day peak suggests that students utilizing the Purple Room might be seeking tutoring before afternoon coursework or assessments, potentially reflecting differences in course scheduling or academic sequencing relative to other rooms.

Figure 5.24

Line Graph of Purple Room Peak Days

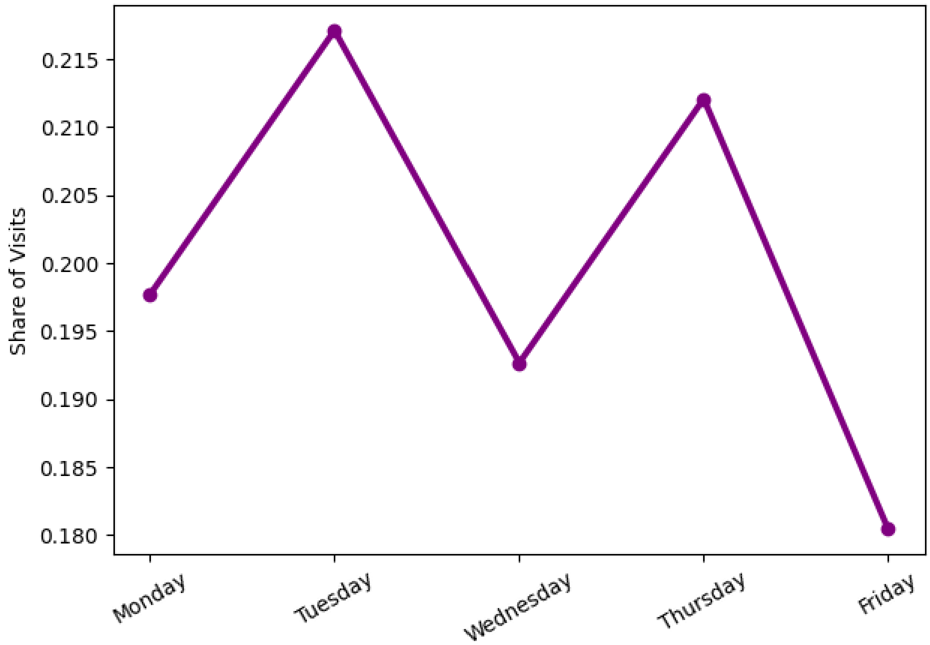
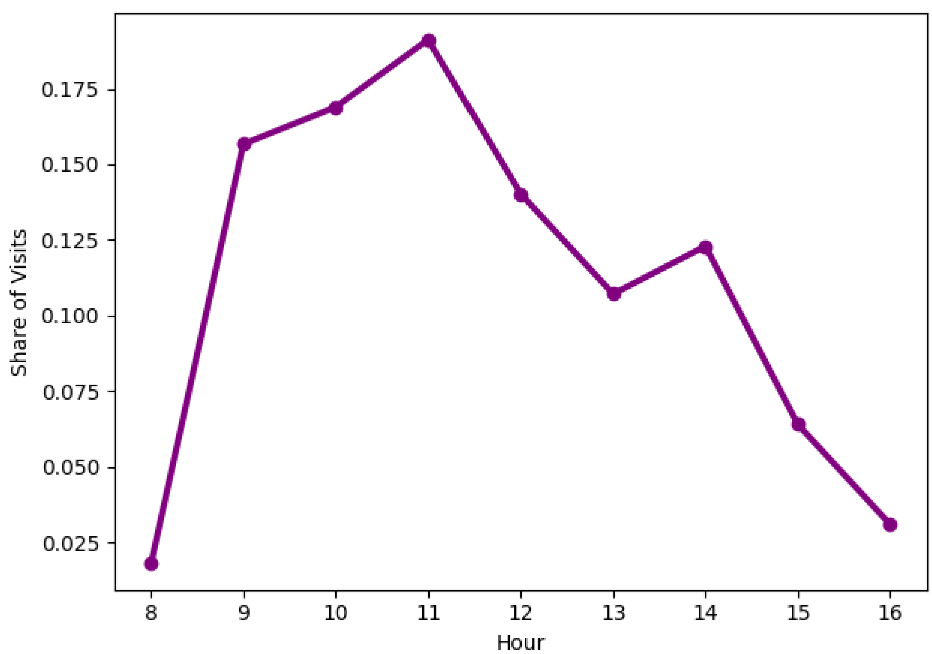


Figure 5.25

Line Graph of Purple Room Peak Check-In Hour



Red Room Weekly Visitation Profile

The Red Room's highest visitation occurred on Tuesdays and Wednesdays. Hourly demand mirrored the broader institutional pattern, with peak activity between 10:00 a.m. and 2:00 p.m. Unlike the Green Room's concentrated 1:00 p.m. spike, the Red Room displayed a more distributed mid-day intensity, indicating sustained demand across multiple contiguous hours.

Figure 5.26

Line Graph of Red Room Peak Days

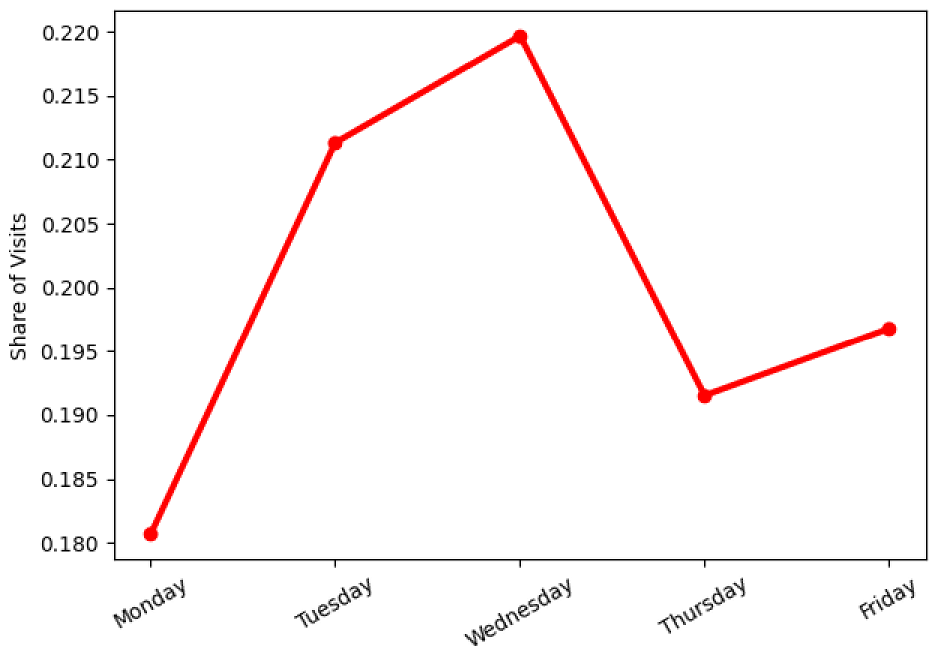
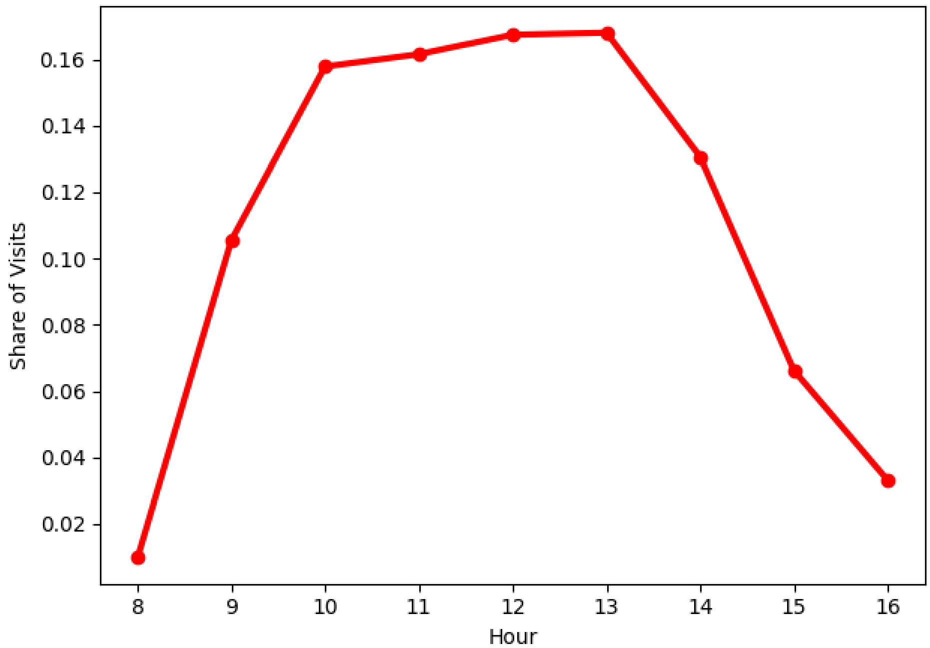


Figure 5.27

Line Graph of Red Room Peak Check-In Hour



Yellow Room Weekly Visitation Profile

The Yellow Room exhibited its strongest attendance on Wednesdays and especially Thursdays. The pronounced Thursday concentration may reflect coordinated assessment timing or assignment cycles in the courses housed within this room. Similar to several other rooms, hourly peaks occurred between 10:00 a.m. and 2:00 p.m., reinforcing the stability of the mid-day demand window across the Math Center.

Figure 5.28

Line Graph of Yellow Room Peak Days

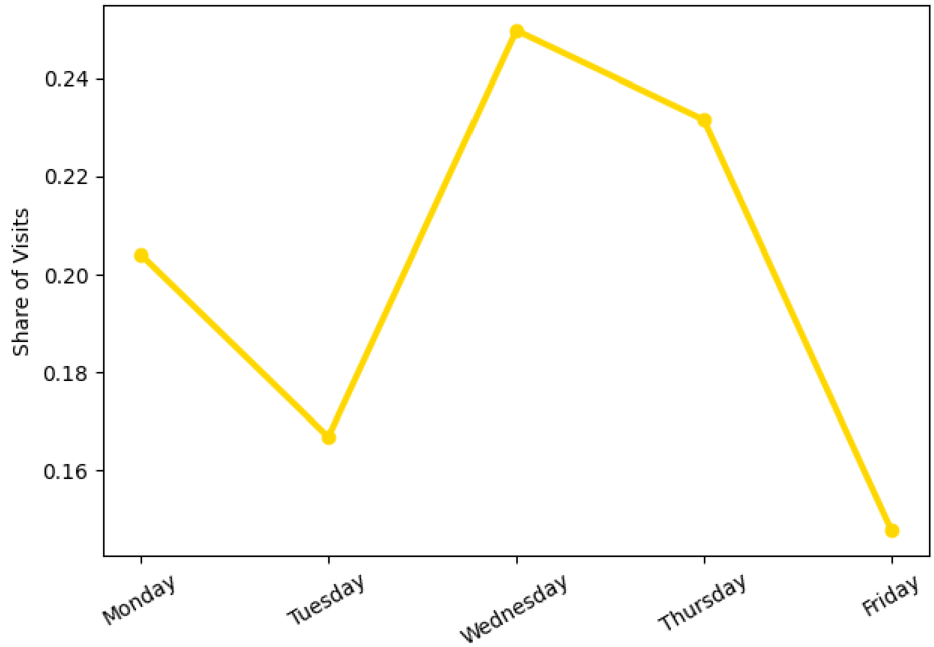
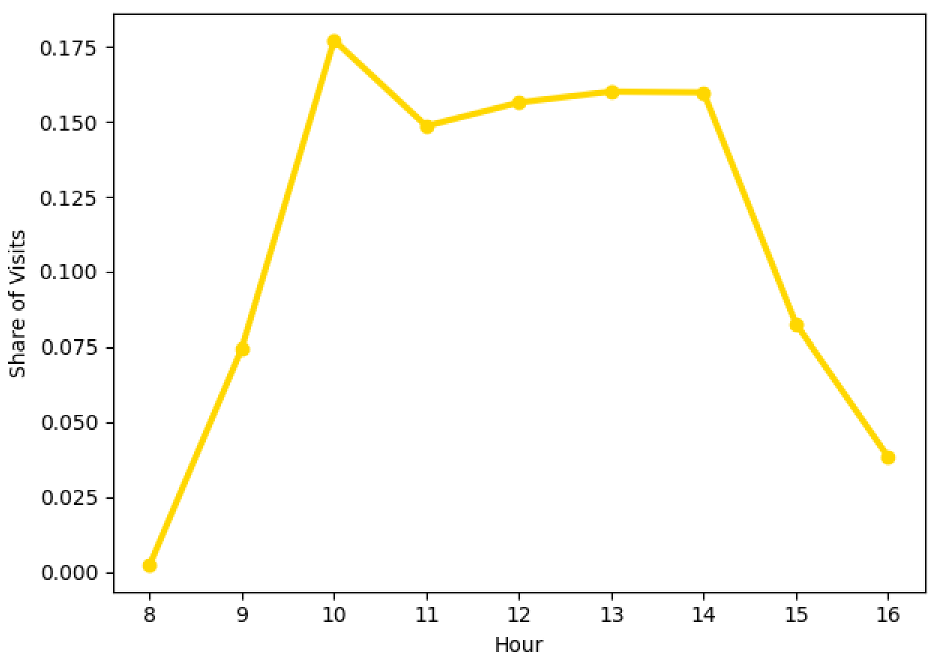


Figure 5.29

Line Graph of Yellow Room Peak Check-In Hour



Orange Room Weekly Visitation Profile

The Orange Room exhibited its strongest attendance on Wednesdays, with Mondays and Tuesdays also contributing. We note that this data is significantly impacted by the addition of Math 1005 in the Fall 25 semester. Similar to several other rooms, hourly peaks occurred between 11:00 a.m. and 2:00 p.m., reinforcing the stability of the mid-day demand window across the Math Center.

Figure 5.30

Line Graph of Orange Room Peak Days

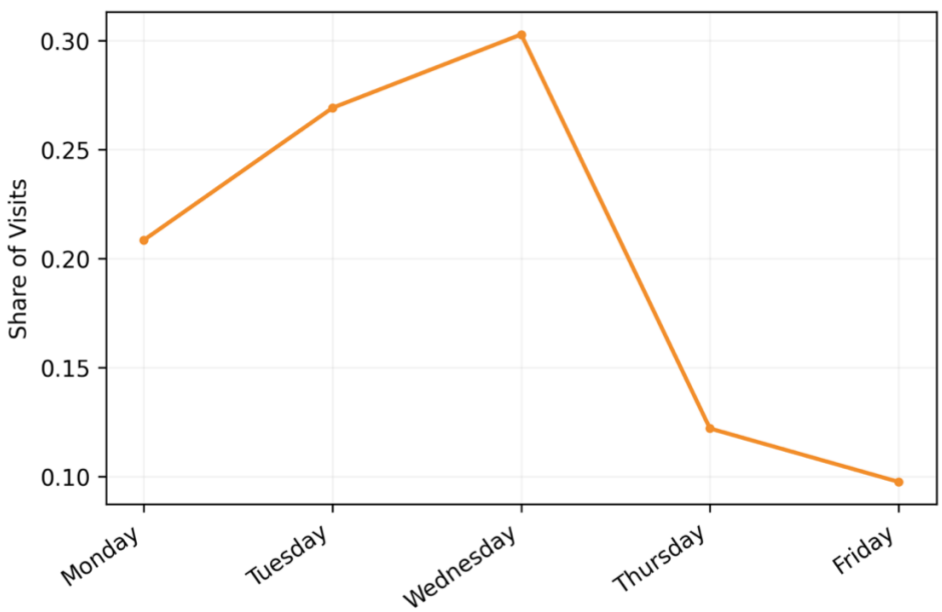
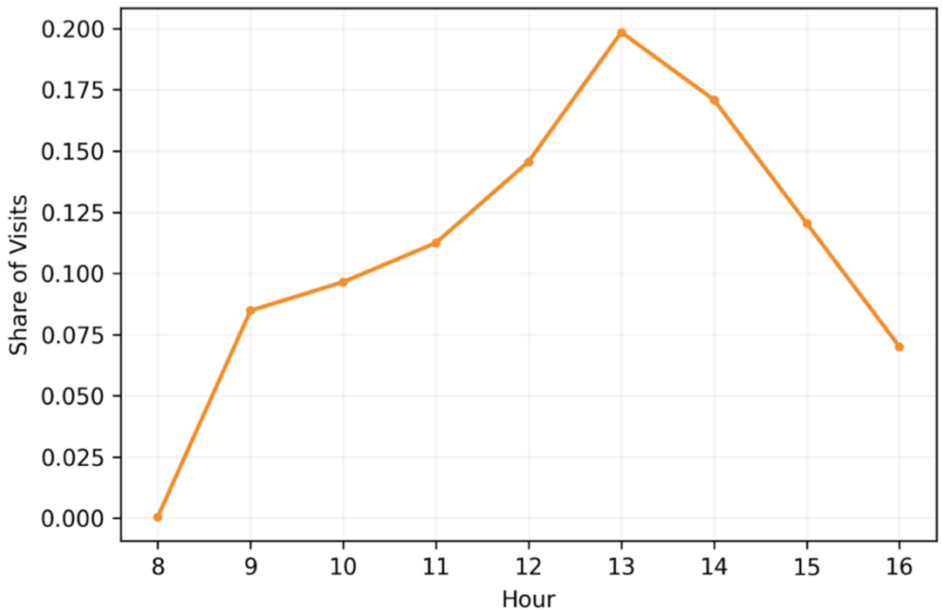


Figure 5.31

Line Graph of Orange Room Peak Check-In Hour



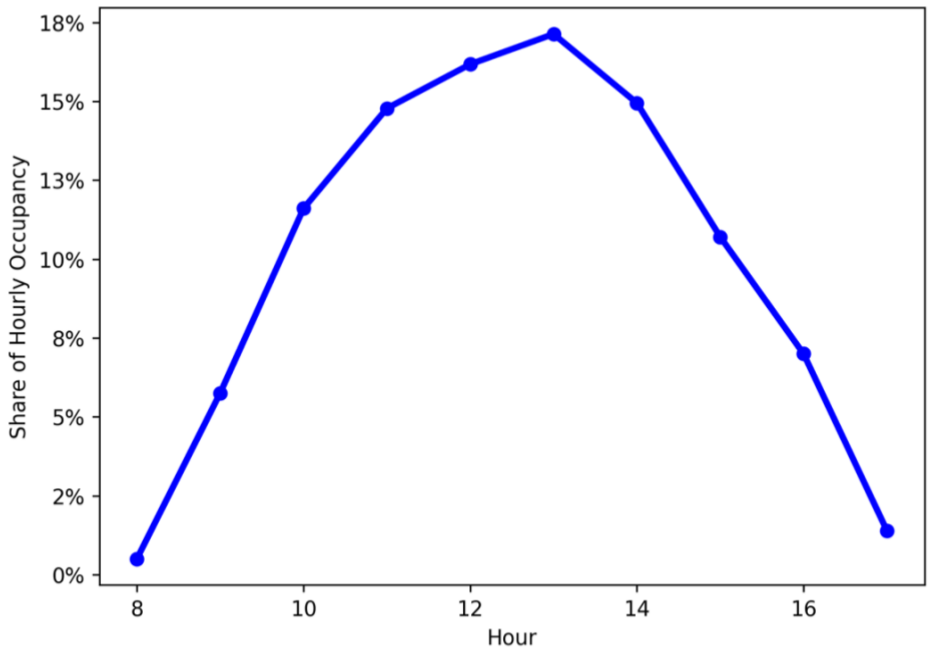
Collectively, the room-level analyses revealed two important structural insights. First, while mid-day (10:00 a.m.–2:00 p.m.) remained the dominant hourly window across nearly all rooms, the specific weekday concentration varied by room. This variation likely reflects course scheduling structures, lecture patterns (e.g., Monday/Wednesday/Friday versus Tuesday/Thursday formats), and assessment timing within curricular clusters. Second, despite these weekday differences, the temporal core of demand consistently centered on late morning to early afternoon hours.

These findings provide evidence that staffing models should account not only for overall daily peaks but also for room-specific weekday rhythms. Aligning tutor expertise and room assignments with these patterned fluctuations might improve service responsiveness while minimizing inefficiencies.

To extend the room-level temporal analysis, we examined hourly occupancy patterns and within semester weekly visitation for each room.

Figure 5.32

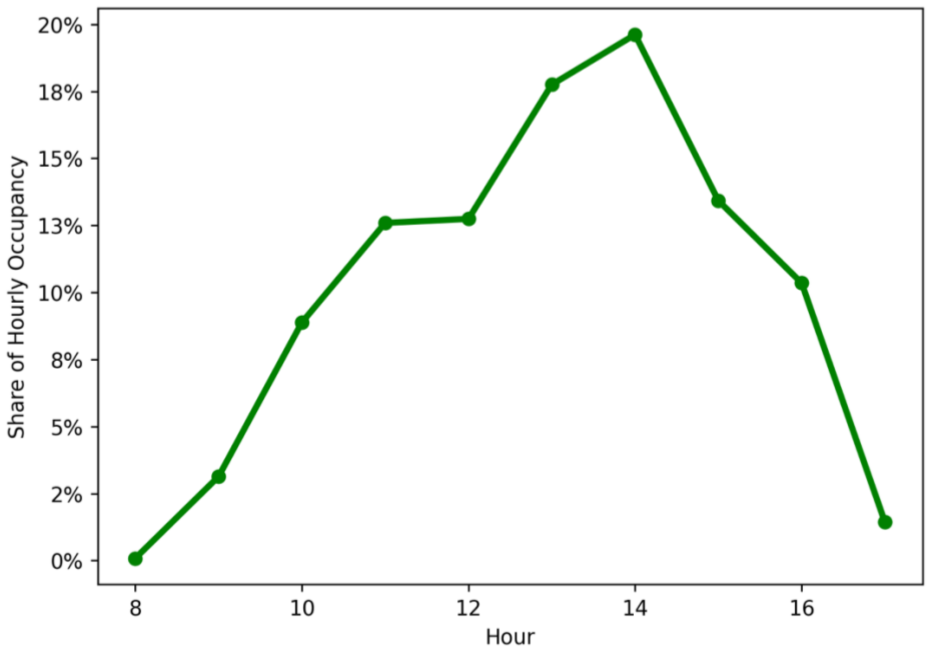
Line Graph of Blue Room Occupancy by Hour



The Blue Room exhibited its highest occupancy between 12:00 p.m. and 2:00 p.m., reinforcing the broader center-wide mid-day concentration. This sustained two-hour peak suggests that demand in this room was both predictable and concentrated during early afternoon transitions.

Figure 5.33

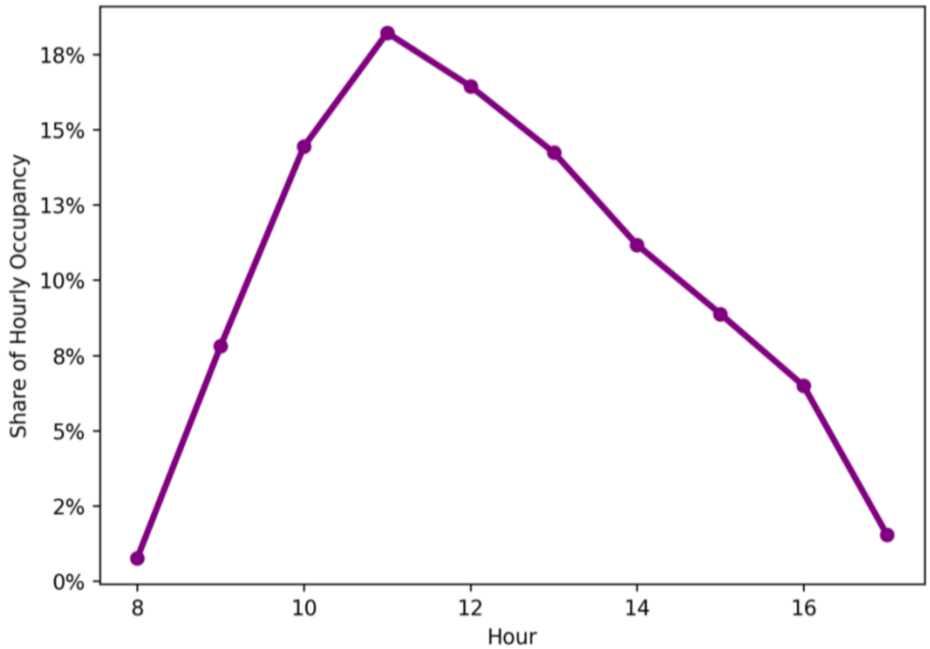
Line Graph of Green Room Occupancy by Hour



The Green Room's highest occupancy occurred between 1:00 p.m. and 2:00 p.m., with a particularly pronounced spike at 1:00 p.m. Compared to other rooms, this peak appeared sharper and more concentrated, indicating a more synchronized arrival pattern likely tied to coordinated course structures or lecture scheduling in the sequence of courses for business, life, and social science majors.

Figure 5.34

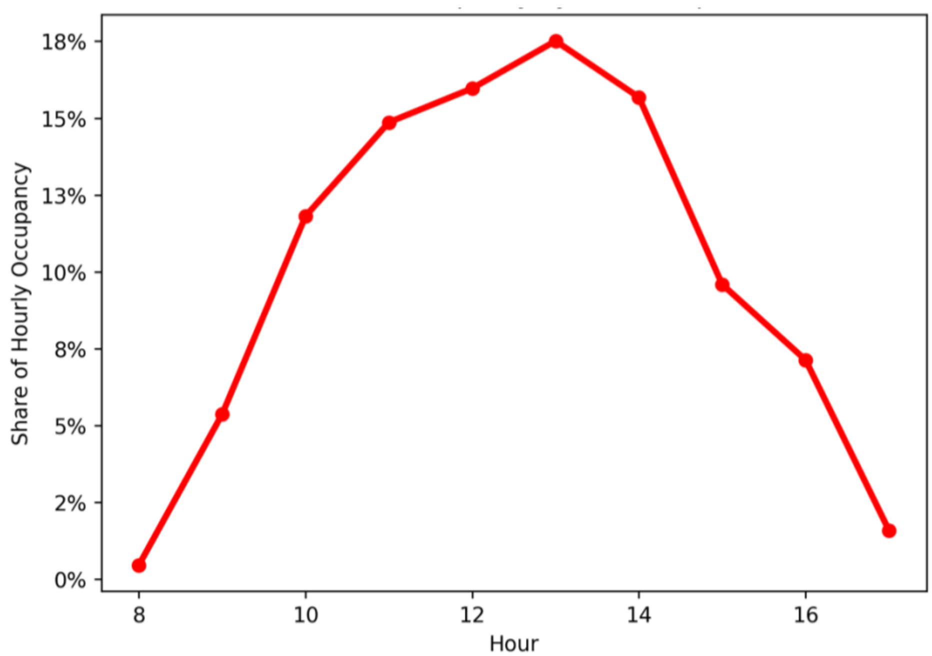
Line Graph of Purple Room Occupancy by Hour



The Purple Room diverged slightly from the early afternoon dominance observed elsewhere. Its highest occupancy occurred between 10:00 a.m. and 12:00 p.m., with peak concentration in the late morning window. This earlier peak might reflect differences in course scheduling or the academic needs of students in more advanced mathematics courses assigned to this space.

Figure 5.35

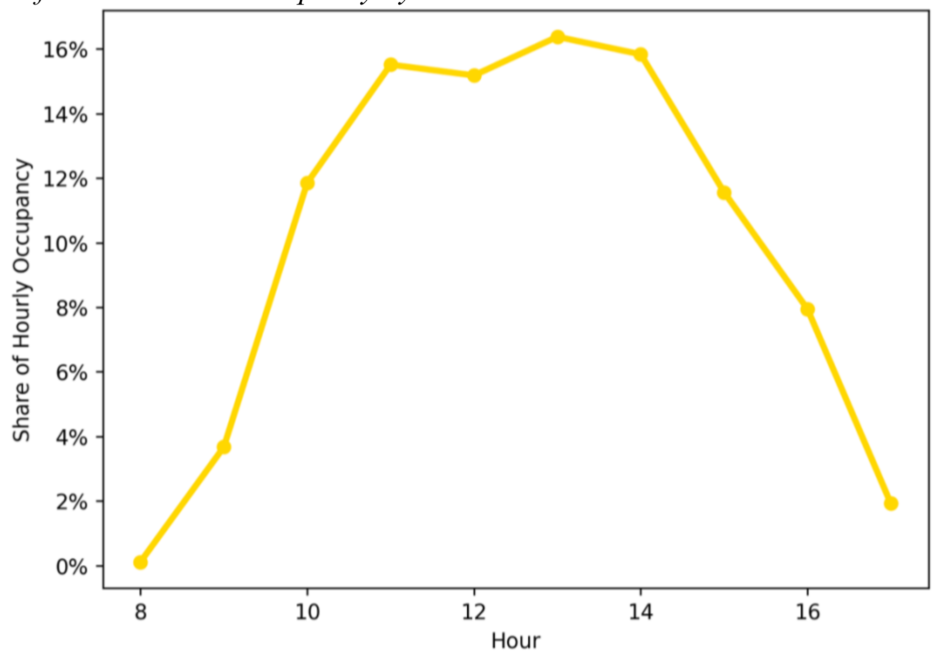
Line Graph of Red Room Occupancy by Hour



The Red Room demonstrated its highest occupancy between 12:00 p.m. and 2:00 p.m., consistent with the institutional mid-day pattern. Unlike the sharper 1:00 p.m. spike seen in the Green Room, the Red Room's peak appeared to be distributed across this two-hour window.

Figure 5.36

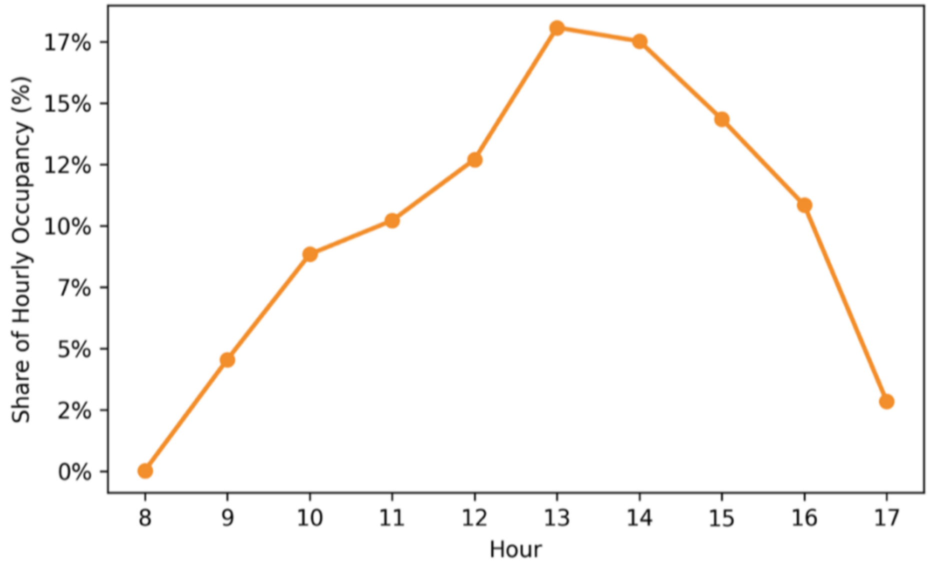
Line Graph of Yellow Room Occupancy by Hour



The Yellow Room showed elevated occupancy spanning 10:00 a.m. through 2:00 p.m., indicating a broader plateau rather than a singular peak hour. This extended window suggested sustained demand across late morning and early afternoon periods.

Figure 5.37

Line Graph of Orange Room Occupancy by Hour



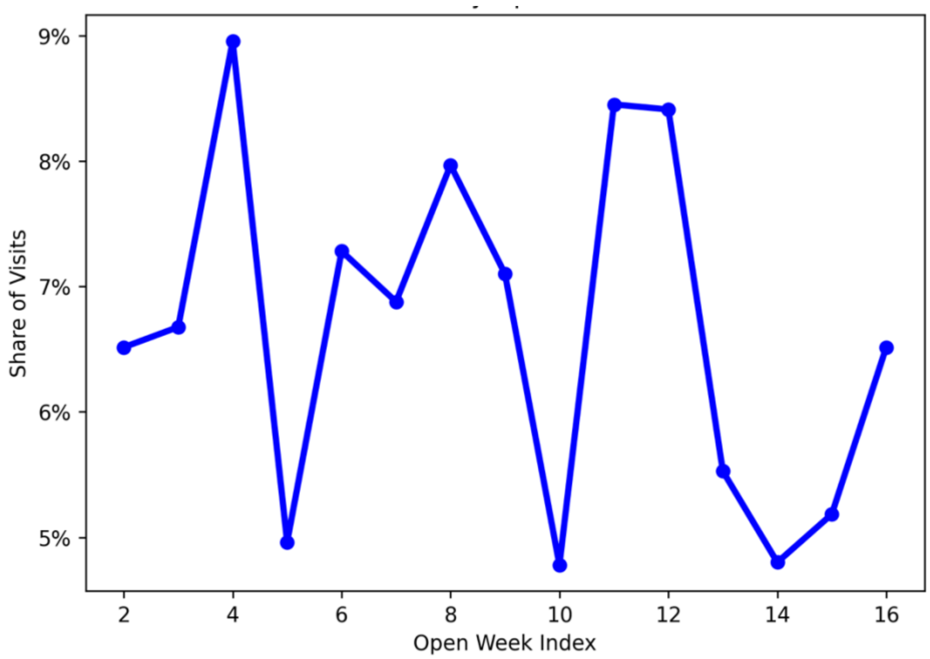
The Orange Room showed elevated occupancy spanning 10:00 a.m. through 3:00 p.m., indicating a peak hour of 1:00 p.m. This extended window suggested sustained demand across late morning and early afternoon periods.

Collectively, these hourly occupancy findings confirm that mid-day remained the dominant service pressure window across rooms, though the precise peak hour varied slightly by room color.

Note as we are about to observe room color occupancy by week, that the graphs will start on week 2. This is because the Math Center does not open until the second week of classes.

Figure 5.38

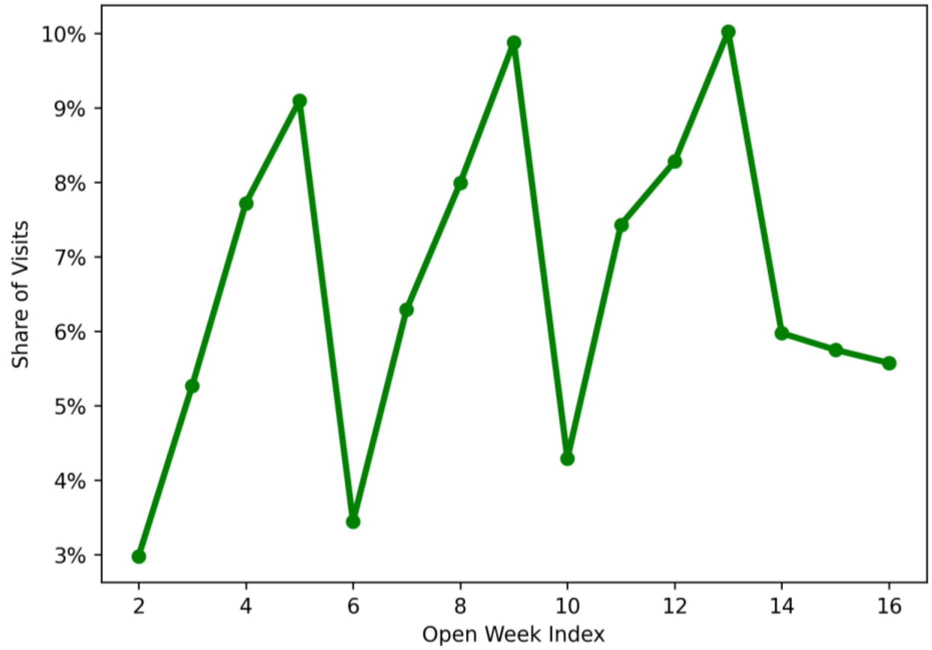
Line Graph of Blue Room Occupancy by Week



The Blue Room demonstrated pronounced visitation spikes in Weeks 3, 11, and 12. In contrast, Weeks 5 and 10 showed substantial declines. This oscillating pattern suggests alignment with specific assessment cycles or assignment clustering within courses housed in this room.

Figure 5.39

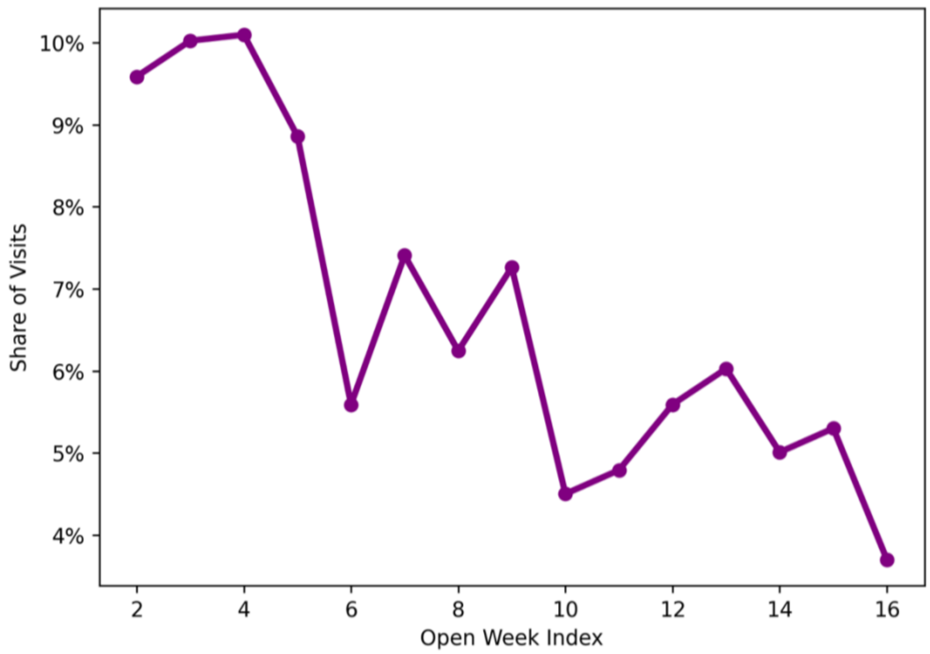
Line Graph of Green Room Occupancy by Week



The Green Room showed peak visitation in Weeks 4, 9, and 13. Notably, Weeks 2, 6, and 10 represent trough periods. The recurrence of multi-peak cycles across the semester suggests structured assessment timing, likely corresponding to coordinated exam schedules in gateway courses.

Figure 5.40

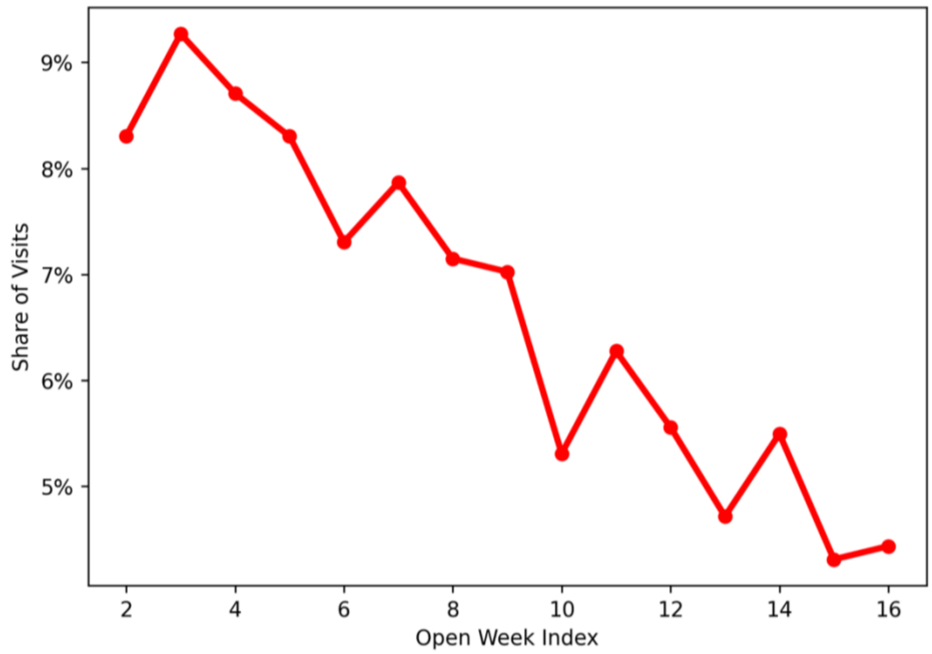
Line Graph of Purple Room Occupancy by Week



The Purple Room exhibited its highest visitation between Weeks 2 and 5, followed by a marked decline thereafter. This front-loaded demand pattern may indicate early-semester adjustment challenges or foundational conceptual bottlenecks in advanced coursework, with support needs tapering once students stabilize academically.

Figure 5.41

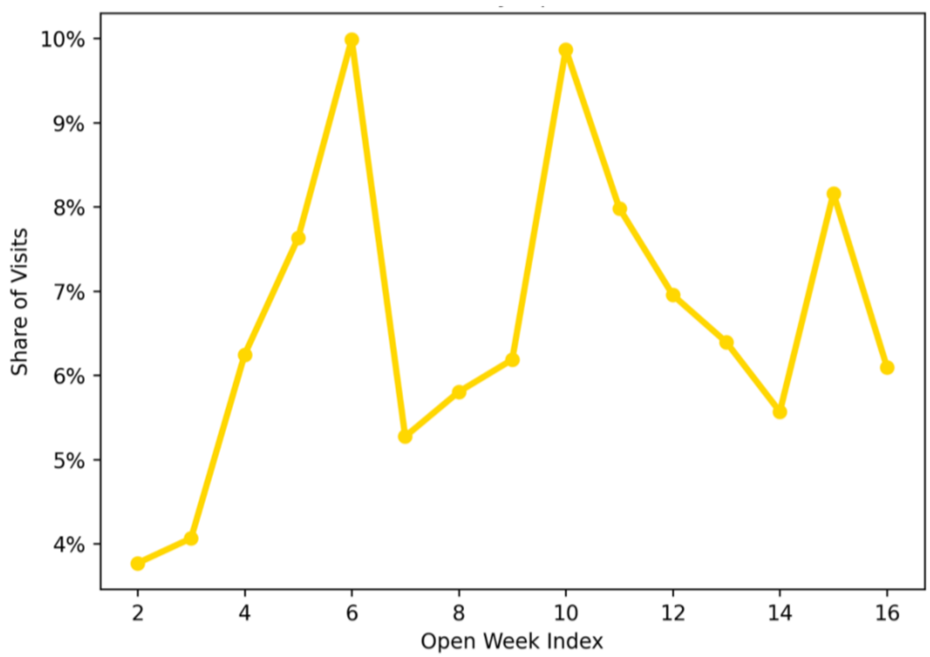
Line Graph of Red Room Occupancy by Week



Like the Purple Room, the Red Room demonstrated elevated visitation during Weeks 2 through 5, followed by a notable decrease. This early-semester concentration suggests that students in courses assigned to this room might require intensive initial support before transitioning to more independent engagement later in the term.

Figure 5.42

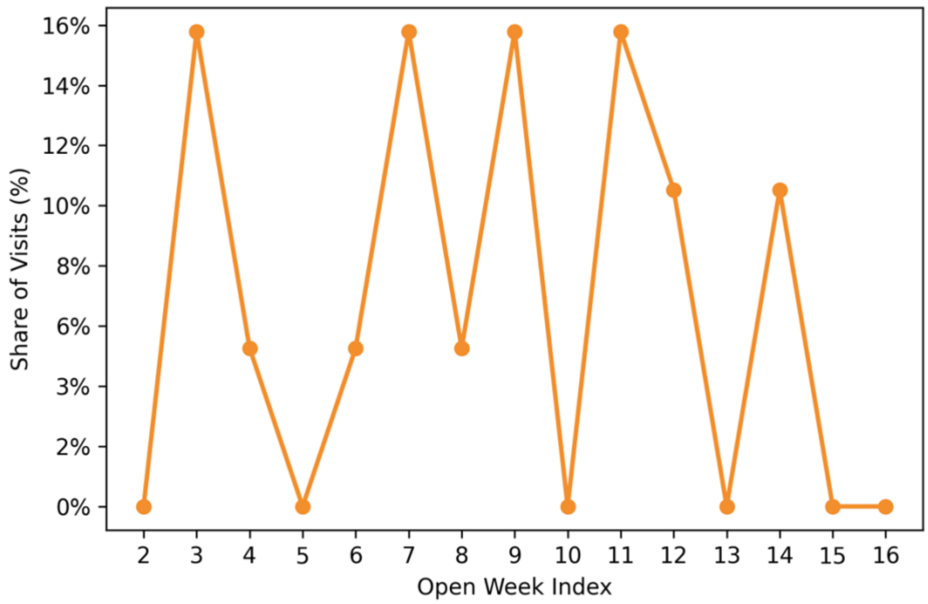
Line Graph of Yellow Room Occupancy by Week



The Yellow Room presented a more distributed weekly pattern, with peaks in Weeks 5, 10, and 15 and troughs in Weeks 2, 7, and 14. This staggered structure indicates repeated assessment-driven spikes throughout the semester rather than a front-loaded or single-cycle pattern.

Figure 5.43

Line Graph of Orange Room Occupancy by Week



The Orange Room presented a zig-zag pattern, with peak week Weeks 3, 7, 9 and 11 and troughs in Weeks 2, 5, 10 and 13. This staggered structure indicates repeated assessment-driven spikes throughout the semester rather than a front-loaded or single-cycle pattern.

When examined together, hourly, and weekly room-level analyses revealed two critical structural dynamics:

1. Hourly Convergence: Across nearly all rooms, peak occupancy occurred between 10:00 a.m. and 2:00 p.m., confirming a strong institutional mid-day service pressure window. While the precise peak hour varied slightly (e.g., 11:00 a.m. in Purple versus 1:00 p.m. in Green), the broader time band remained consistent.
2. Weekly Divergence: In contrast to hourly convergence, weekly patterns varied substantially by room. Some rooms (Purple and Red) exhibited early-semester

concentration, others (Green and Blue) showed cyclical mid-semester spikes, and the Yellow Room displayed repeated assessment aligned peaks across the term.

These findings underscore the need for dynamic staffing models. While mid-day coverage should remain robust across all rooms, weekly staffing intensity may need to be adjusted, if possible, based on course-specific assessment cycles and room-level visitation rhythms. Such differentiation would allow the Math Center leadership to align tutor deployment more precisely with empirically observed patterns of demand rather than applying uniform semester long staffing patterns.

To examine assessment driven demand with greater precision, we conducted an event time analysis centered on coordinated exam dates. For each coordinated course and each exam instance, we computed daily visit counts on weekdays from seven days prior through two days following the exam (RelDay = −7, …, +2; RelDay = 0 corresponds to the exam date). Visit counts were then aggregated across exam instances to obtain an average number of visits per exam for each relative day. All analyses relied exclusively on baseline operational hours (check-in and checkout ≤ 5:30p.m.), excluded evening tutoring and review sessions, and removed sessions exceeding 180 minutes to preserve comparability with prior sections.

To contextualize exam-driven fluctuations, we constructed a non-exam baseline for each course. This baseline represented the mean daily visits on days not included in any exam window for that course. We then computed an exam "lift" metric defined as:

$$\text{Lift}=(\text{BaselineMean}/\text{AvgVisitsPerExam})-1.$$

Lift values quantify the proportional increase (or decrease) in visitation relative to typical non-exam days. Positive lift indicates unusual congestion associated with exam timing, where near-zero values suggest little deviation from baseline patterns.

Across coordinated courses including MATH 1503, 1523, 1643, 1743 1823, and 1914 (we only included these courses as these were the only courses we had specific exam data) relative day curves consistently demonstrated increases in visitation as RelDay approaches 0. This upward slope indicates a clear pre-exam demand buildup. For the courses 1503, 1523 and 1743, peak visitation occurs at RelDay −1 or −2, suggesting that students were most likely to seek tutoring support one to two weekdays prior to the exam rather than on the exam day itself. Operationally, this lead-time signal was particularly important. If the maximum lift occurs at RelDay −1 or −2, staffing density should be increased during those specific weekdays rather than concentrated solely on the exam date.

Figure 5.44

Line Graph of 1823 Exam-aligned Demand

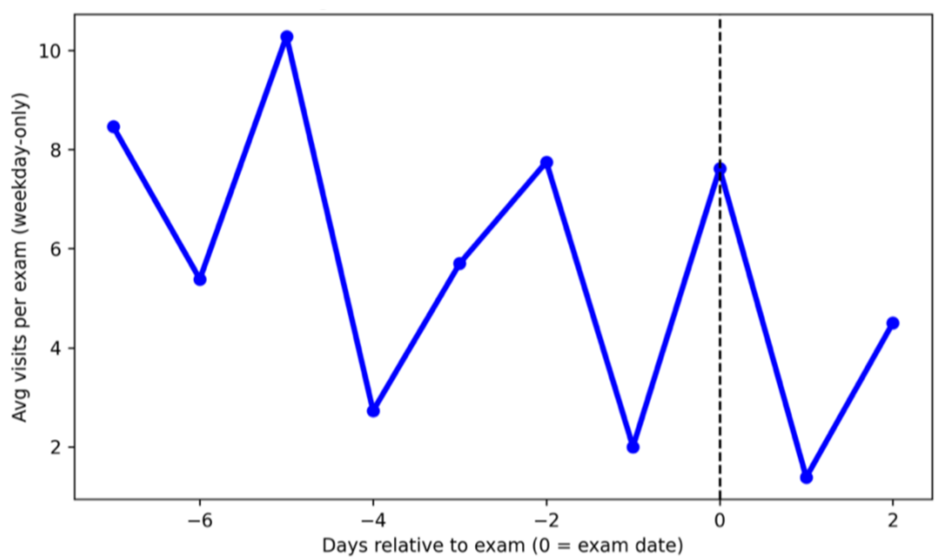


Figure 5.45

Line Graph of 1914 Exam-aligned Demand

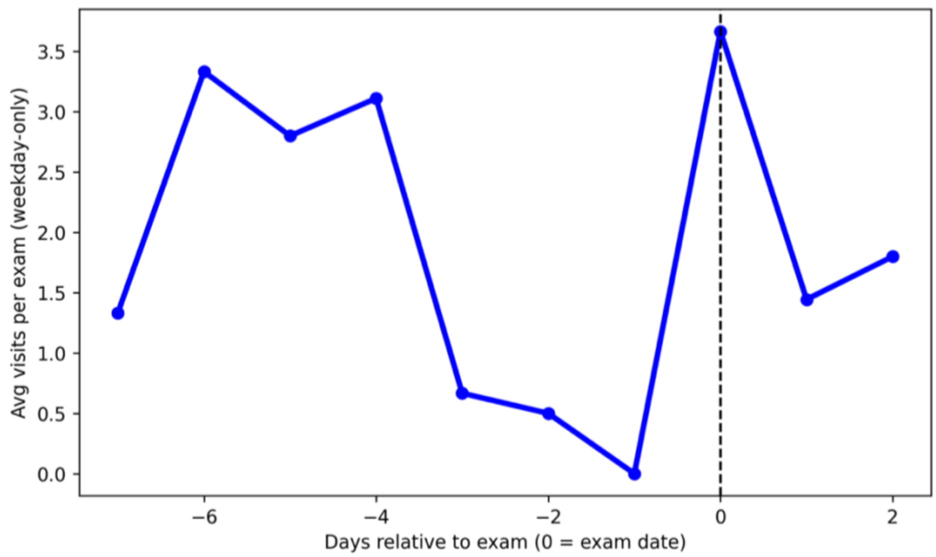


Figure 5.46

Line Graph of 1643 Exam-aligned Demand

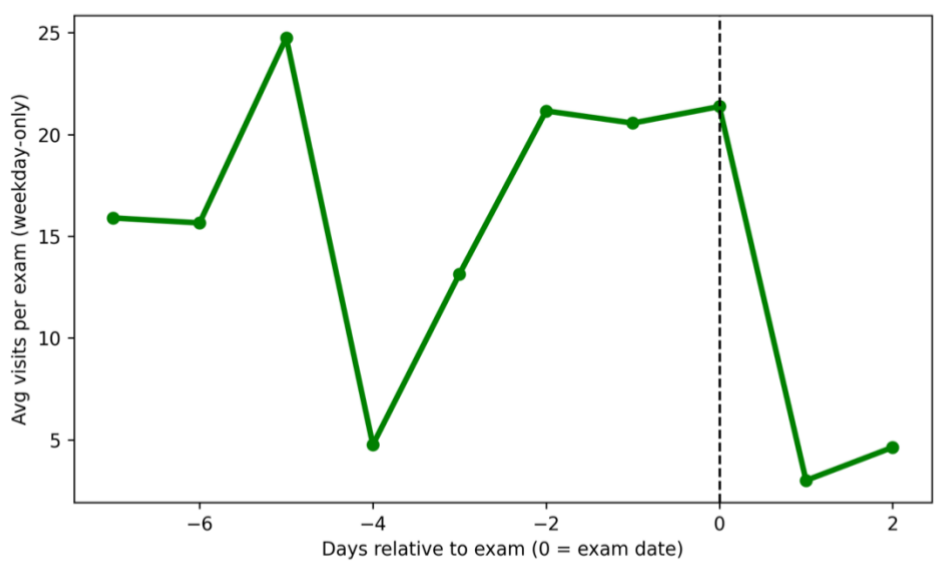


Figure 5.47

Line Graph of 1743 Exam-aligned Demand

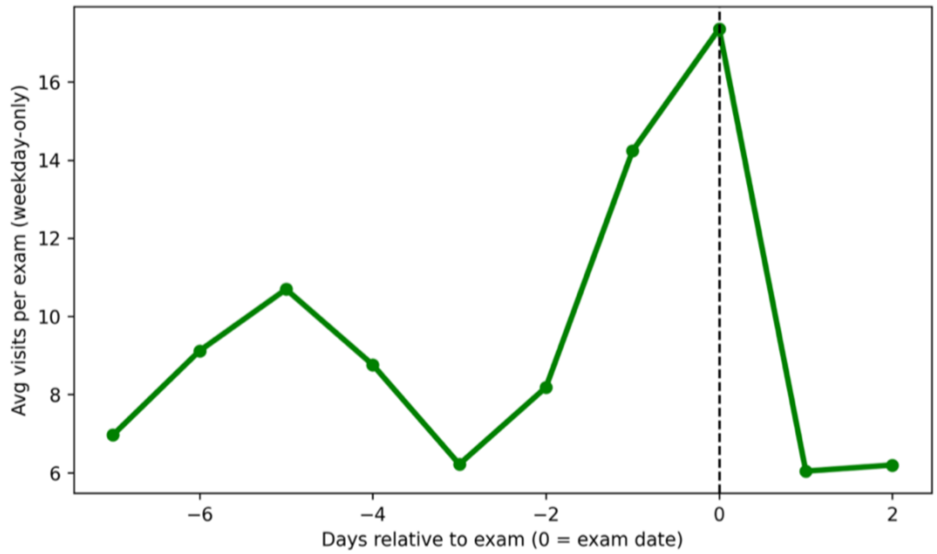


Figure 5.48

Line Graph of 1503 Exam-aligned Demand

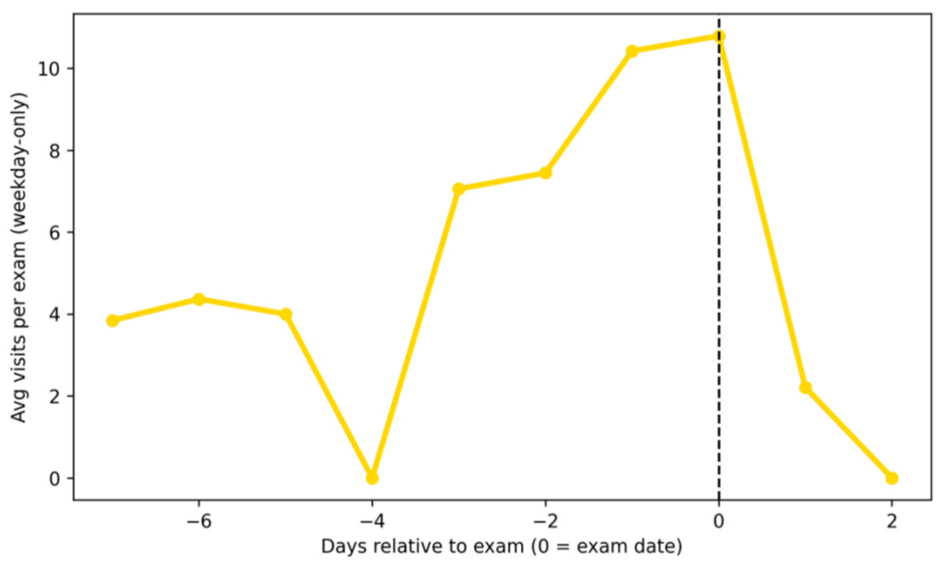
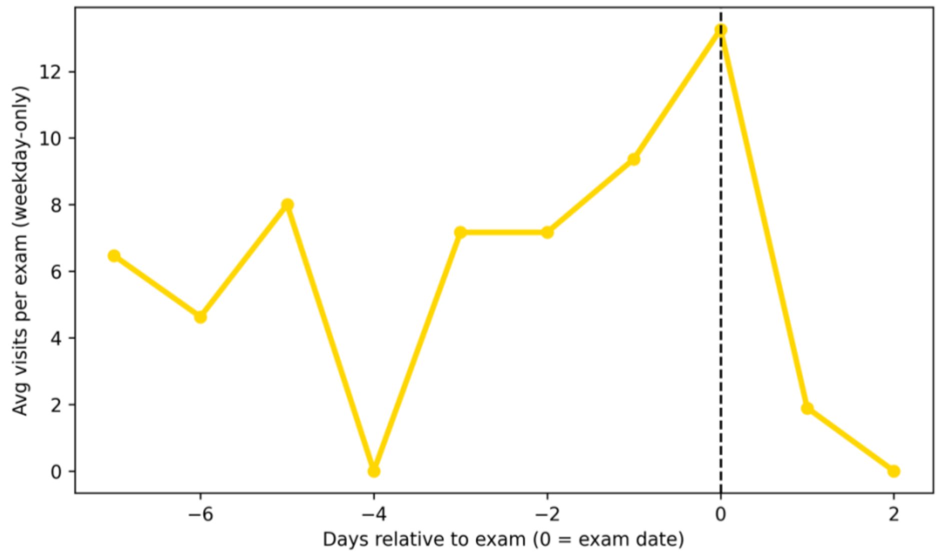


Figure 5.49

Line Graph of 1523 Exam-aligned Demand



The accompanying bar chart ranks coordinated courses by exam day lift relative to baseline. Courses with the highest positive lift representing the strongest exam-related congestion relative to their typical daily demand. This ranking provides administrators with a comparative indicator of which courses produced the most acute exam-driven pressure and therefore might warrant proactive staffing adjustments, structured review sessions, or targeted resource allocation.

Figure 5.50

Bar Graph of Course Exam-day Lift vs Non-Exam Baseline

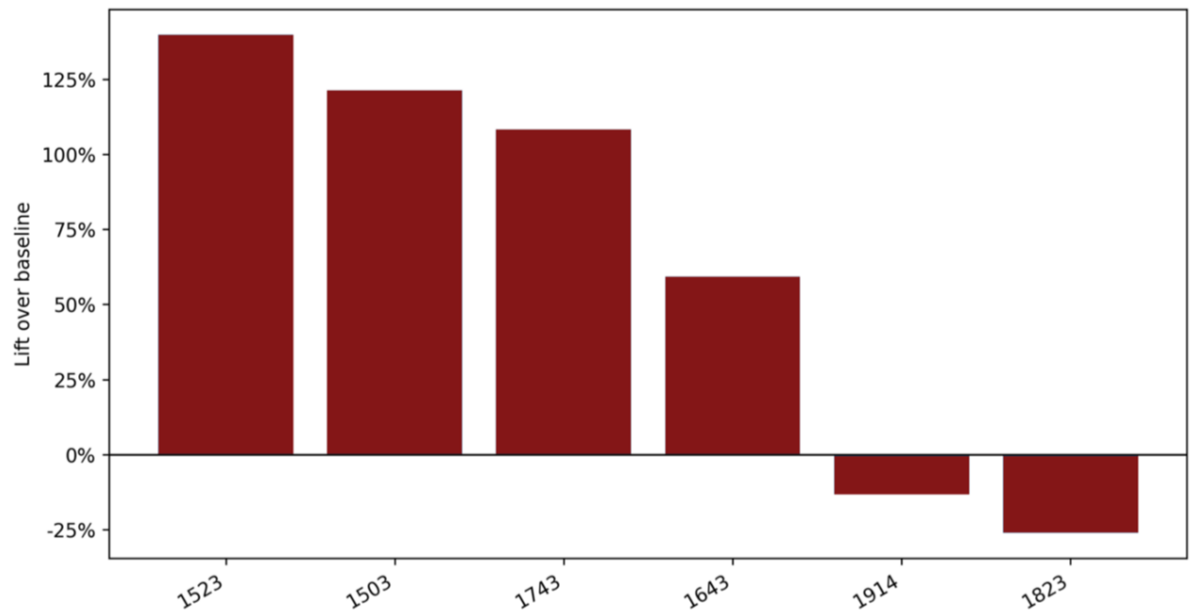


Table 5.1

Average Course Lifts from Exam Dates

Course	Room	Lift(RelDay=0)	AvgExamDayVisits	BaselineMean	ExamsCount
1523	yellow	139.9%	13.26	5.53	19
1503	yellow	121.4%	10.79	4.87	19
1743	green	108.3%	17.36	8.34	25
1643	green	59.3%	21.37	13.41	19
1914	blue	-13.2%	3.67	4.22	9
1823	blue	-26.2%	7.62	10.31	13

Table 5.2

Peak Course Lifts from Exam Dates

Course	Room	PeakRelDay	PeakAvgVisitsPerExam	BaselineMean
1823	blue	-5	10.29	10.31
1914	blue	0	3.67	4.22
1643	green	-5	24.75	13.41
1743	green	0	17.36	8.34
1503	yellow	0	10.79	4.87
1523	yellow	0	13.26	5.53

It is important to interpret these curves conservatively. Because the analysis excluded after dark sessions (extended time in which the Math Center was open beyond normal operating times) and coordinated review programming often occurs outside regular Math Center hours, the measured increase (which we called lift above) likely underestimates total exam-driven demand. However, while the magnitude of congestion might be understated, the timing of the buildup (PeakRelDay) remains highly informative for daytime operational planning.

In sum, the event-time analysis confirmed that tutoring demand systematically intensified in the days immediately preceding coordinated exams. The strongest implication was not merely that exams increase demand, but that this increase followed a predictable lead time pattern. Recognizing and planning for this pre-exam buildup might enable the Math Center to align daytime staffing capacity with empirically observed student preparation behavior.

Across the temporal analyses presented in this section, two complementary signals emerged: check-in flow (i.e., arrivals) and occupancy-based load (i.e., students present over time). While related, these metrics captured distinct dimensions of service demand. Arrivals indicate when students initiate tutoring interactions; occupancy reflects the cumulative burden placed on staffing resources by overlapping visits and sustained engagement windows.

From a staffing perspective, occupancy-based load is often the more informative indicator of resource pressure. A room may experience only moderate arrival volume yet still require substantial tutor coverage if sessions are lengthy and overlap across multiple hours. In such cases, the strain on staffing is driven not by the number of students entering the space, but by how long they remain and how their visits coincide. Conversely, a brief surge in arrivals may not generate significant operational pressure if visit durations are short and distributed.

The following two figures synthesize these signals into a semester-level staffing playbook for each room band: average visits per day by open week, and average occupancy-hours per day by open week.

Figure 5.51

Line Graph of Room Average Visits per Day

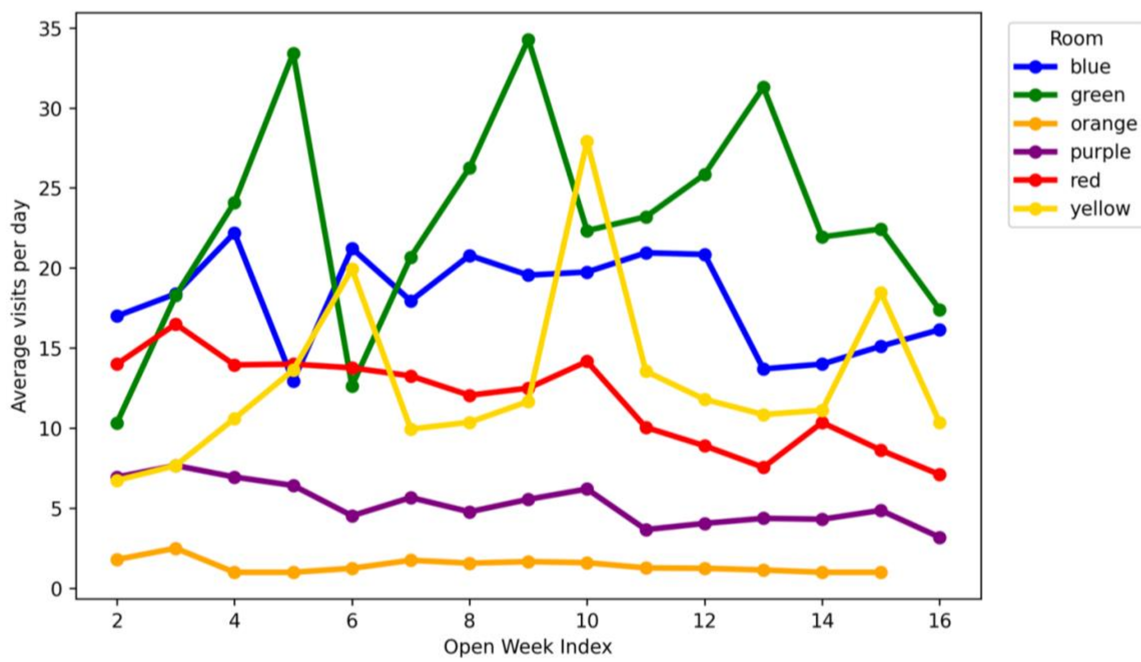
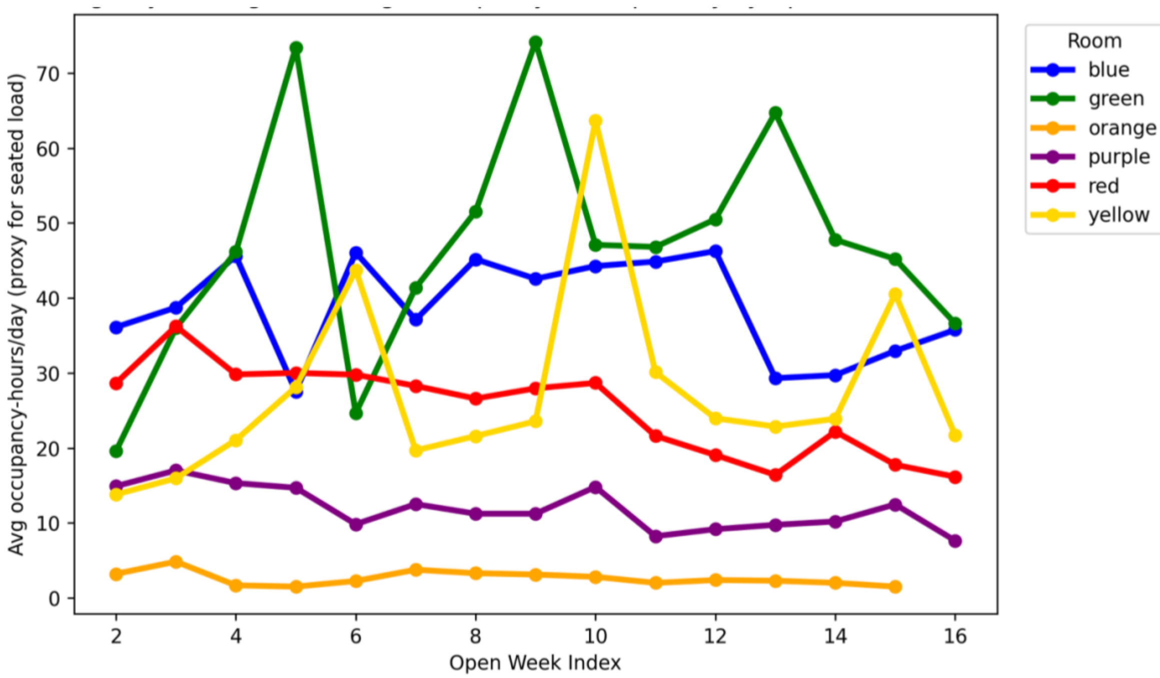


Figure 5.52

Line Graph of Room Average Occupancy hours



Together, Figures 5.51 and 5.52 provide actionable guidance for dynamic staffing allocation across the semester. Rooms with pronounced peaks in visits per day represented predictable surge periods often aligned with assessment cycles or coordinated exams. These spikes signal when foot traffic increased, and queue formation risk rose. In contrast, rooms with elevated occupancy hours over multiple consecutive weeks indicate sustained load, where tutoring interactions were longer or more overlapping. Such patterns suggest that staffing needs remain elevated even if arrival counts appear stable.

The distinction between these two curves is critical. The visits per day curve should be used to anticipate increases in student arrivals and manage intake capacity. The occupancy hours curve, however, should guide decisions about coverage length and depth. A week characterized by high occupancy hours indicates that students are remaining longer or overlapping more frequently, which may require additional tutors, extended coverage windows, or reallocation of expertise even if arrivals do not spike dramatically.

In combination, these complementary measures move staffing decisions beyond simple volume metrics. By integrating flow (arrivals) with load (occupancy), administrators can more accurately align tutor deployment with the true temporal structure of demand across rooms and weeks.

Temporal Attendance Pattern Data

The third research question guiding this analysis was:

What are the distinct attendance patterns of individual students at the Math Center, and what course and temporal factors correspond to these patterns?

While the first two research questions examined aggregate volume and temporal flow at the center and room-levels, this question shifted the unit of analysis to the student-semester level. The objective was to identify meaningful patterns of individual engagement and to determine how those patterns corresponded to course affiliation and timing within the semester.

To address this question systematically, several sub-questions guided the analysis. First, what was the average number of visits to the Math Center per student among those who visited at least once during a semester? Second, how did the frequency of visits vary across different student subgroups, such as by course affiliation (operationalized through dominant room band) or by the timing of the student's first visit? Third, could distinct patterns of MLC usage be identified based on visit frequency, timing, and duration, and if so, what were the defining characteristics of these groups? Fourth, what was the distribution of different user profiles within the overall student population, and did this distribution vary across courses? Fifth, was there a relationship between the timing of a student's first visit and their likelihood of belonging to a particular user profile? Finally, how did the timing of visits relate to subsequent engagement patterns within the same semester?

We start this section by establishing the baseline distribution of student-level engagement within a semester. The analytic unit is the student semester, meaning that each student was observed separately within each semester in which they were enrolled. For example, if a student visited the Math Center in both Fall 2023 and Spring 2024, those observations were treated as two distinct cases. This approach allowed engagement patterns to be examined within the context of a specific academic term rather than aggregated across time.

The analysis was restricted to baseline hours (weekdays with check-in and checkout at or before 17:30). As previously noted, sessions longer than 180 minutes were excluded to maintain consistency with prior sections. The orange room was included in this student-level analysis, while the grey room was excluded. The grey room captured visits that were not associated with a particular course or a course that the Math Center does not serve.

To understand what typical tutoring engagement looks like, we began with the distribution of the number of visits made by each student within a semester, restricted to students who visited at least once. This distribution was highly right-skewed. A substantial proportion of students attended only once or a few times, while a smaller subset returned repeatedly throughout the term. This skewness mirrors patterns observed at the aggregate level, but here it was visible at the individual level of participation.

To further characterize this distribution, we used the empirical cumulative distribution function (ECDF). An ECDF does not display the number of students with exactly a given visit count, as a histogram would. Instead, it shows the proportion of students who had a given number of visits or fewer. For example, if the ECDF value at three visits is 0.72, this indicates that 72 percent of students visited the MLC three times or fewer in that semester. Operationally, the ECDF provides a clear translation from raw counts to cumulative participation patterns. It helped distinguish one-time users from regular and high frequency users and served as a natural bridge from descriptive statistics to actionable student usage buckets.

Figure 5.53

Bar Chart of Visits per Student

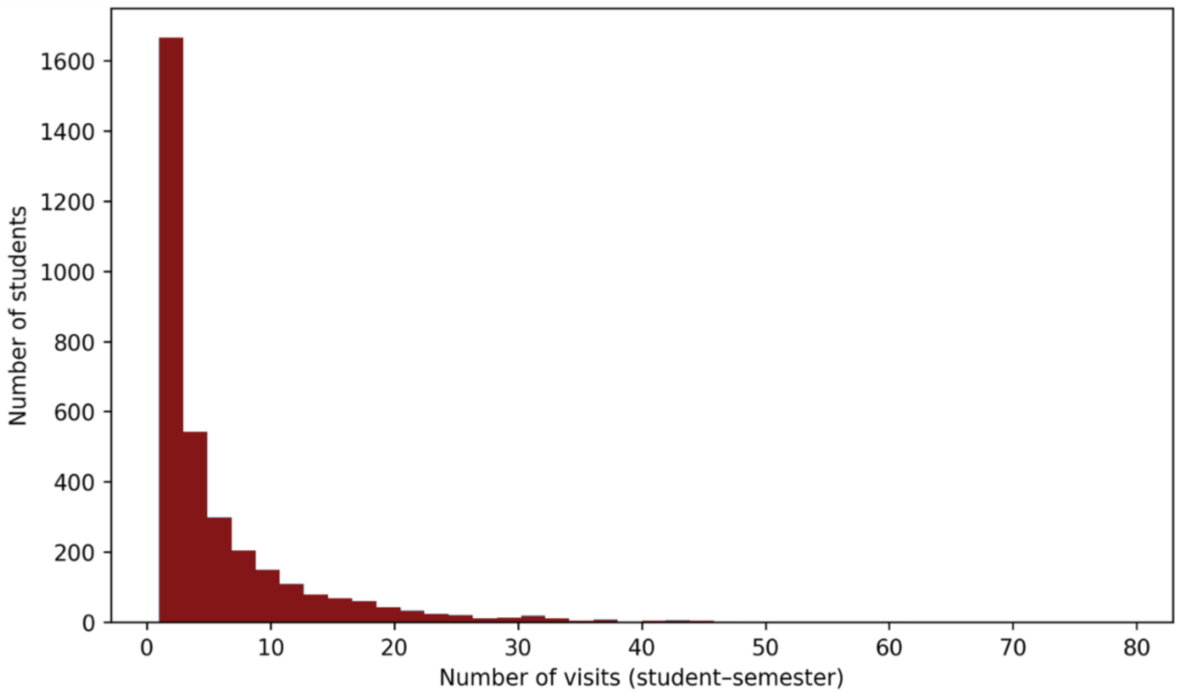
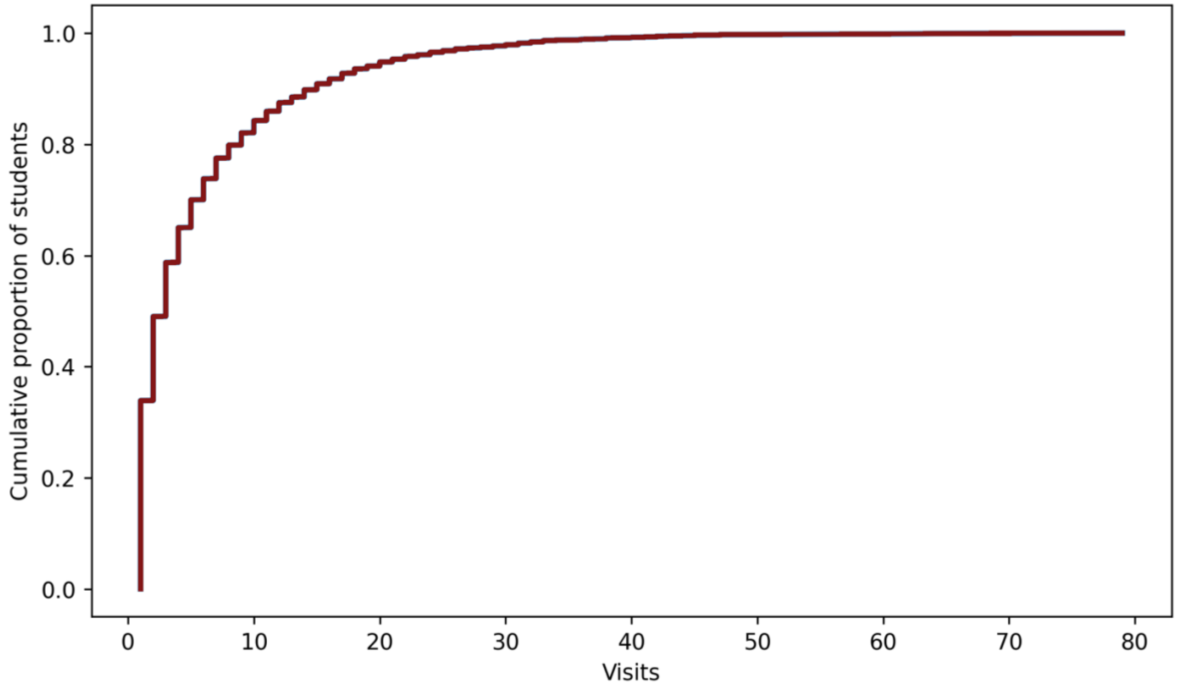


Figure 5.54

Line Chart of ECDF of Visits per Student Semester



The next part of the third research question introduced student-semester usage profiles as a structural shift in analytic perspective. Rather than treating visits as isolated events, this phase conceptualized attendance as patterned behavior at the level of the individual student within a given semester. The analytic unit was therefore the student semester. A student might have belonged to one profile in a fall term and a different profile in a subsequent spring term, reflecting changes in course context, academic demands, or engagement strategies.

Profiles were constructed to be mutually exclusive through a priority assignment framework. Each student–semester received exactly one label, ensuring interpretive clarity and preventing overlapping classifications. The profiles were defined using five behavioral dimensions: frequency (total number of visits within the semester), persistence (number of distinct open weeks with at least one visit), timing (week of first visit), session depth (mean minutes per visit), and assessment concentration.

To avoid arbitrary threshold selection, cutpoints were anchored to the empirical distribution of the dataset. One-Time Visitors are those who visited exactly once in that semester. Occasional users were typically 2-3 visits and so totals were below the 50^{th} percentile. We stopped before intersecting the group of One-Time Visitors. For the Long-Session Occasional Users we took a subset of the Occasional users whose mean minutes per visit were at or above the 75^{th} percentile. Consistent Users were those from the 50^{th} to 75^{th} percentile in visit totals. Exam-Oriented Users were identified via a temporal clustering. Finally, Super Users are those who visited above the 75^{th} percentile. These thresholds were reported explicitly in the summary output, ensuring transparency and reproducibility. By defining high intensity groups relative to the observed behavioral tail rather than imposing an external standard, the classification remains descriptive of actual participation patterns in the Math Center.

Figure 5.55 presents the overall distribution of student-semester profiles. This figure addresses the foundational question of what types of users exist within the Math Center population and how substantial the long tail of high-intensity participation was. If one-time and occasional users dominated the distribution, the Math Center functioned primarily as a situational or episodic support service for many students. If consistent and sustained profiles represented a meaningful proportion of the population, the Math Center operated as an ongoing supplemental learning environment for repeat help-seeking. The relative size of each profile therefore anchored the broader interpretation of the center’s institutional role.

Figure 5.55

Bar Chart of ECDF of User Profile Distribution

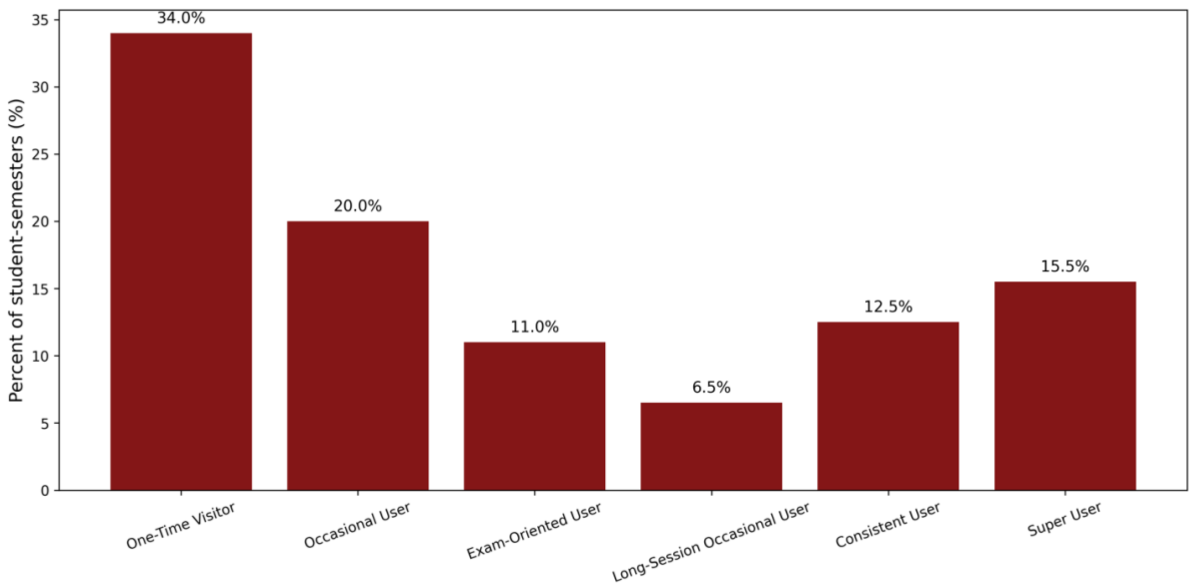


Figure 5.56 displays profile composition by semester. This visualization addressed whether cohorts differed structurally across academic terms. Shifts in the proportion of exam-oriented or sustained engagement profiles may reflect differences in assessment timing, instructional modality, policy changes, or broader institutional conditions. These temporal comparisons provided context for later connections to coordinated exam structures.

The next figure presents profile composition by dominant room band. This comparison seems particularly consequential for administrative planning. Differences in profile composition across room bands indicate that engagement intensity was not evenly distributed across curricular groupings. Rooms with larger proportions of sustained or high intensity profiles require more stable staffing models and deeper tutor expertise. Rooms dominated by one-time or occasional usage might require greater triage capacity and rapid diagnostic support. A chi-square test confirmed that profile composition differed significantly by room band, providing statistical justification for room specific staffing strategies rather than uniform allocation.

Figure 5.56

Stacked Bar Chart of Profile Composition by Semester

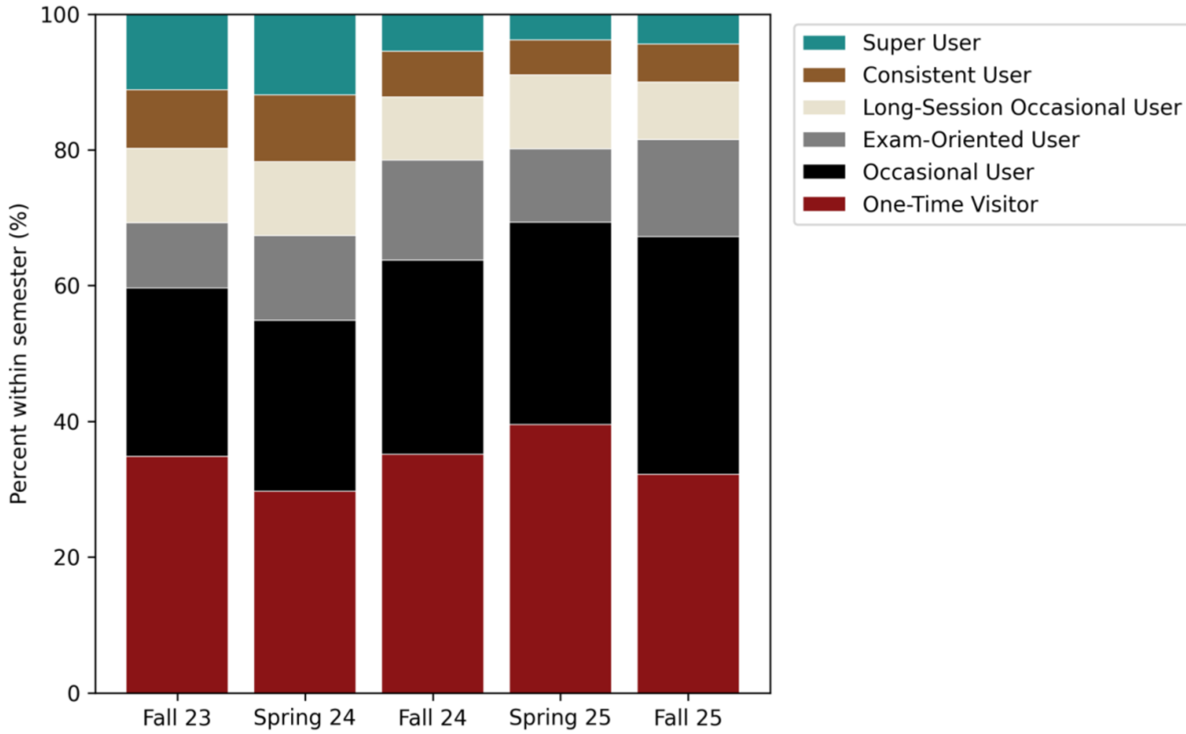
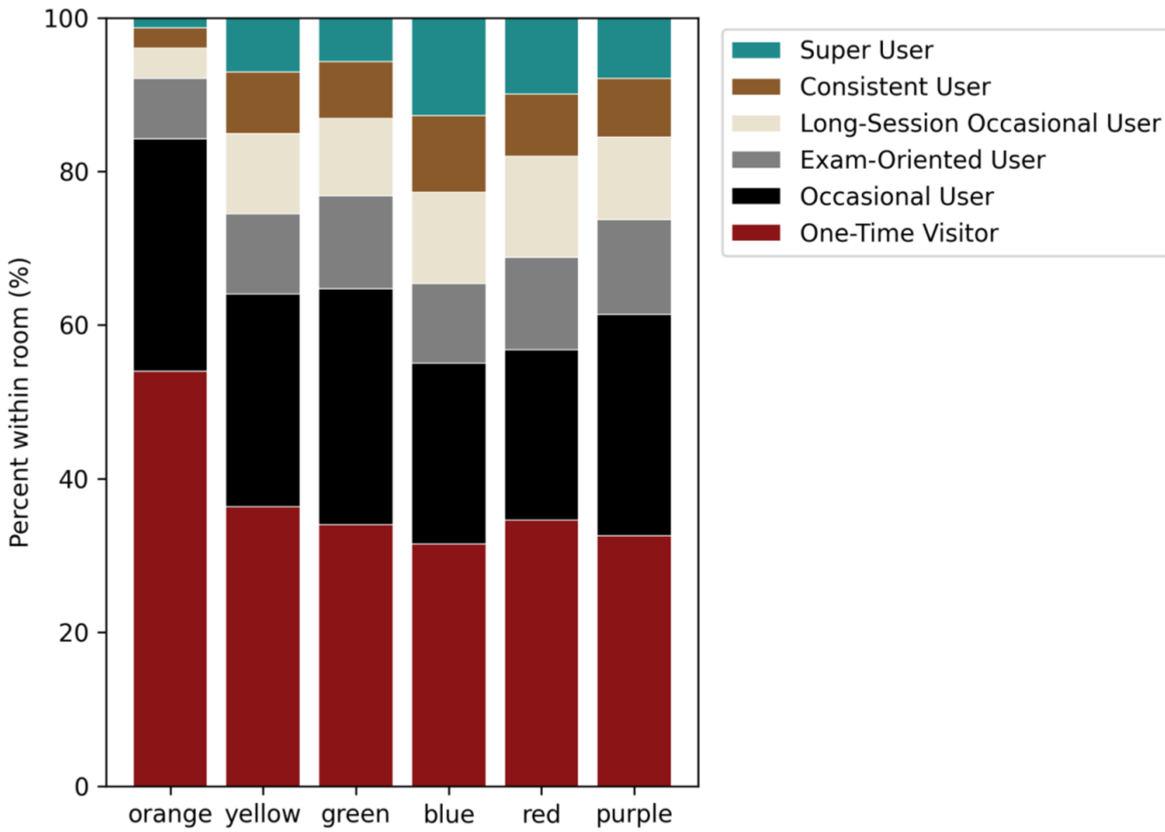


Figure 5.57

Stacked Bar Chart of Profile Composition by Dominant Room Color



The figure examining first visit timing by profile addresses whether early entry into the MLC corresponded to sustained engagement. Profiles characterized as consistent or sustained should exhibit earlier first visits, reflecting routinized engagement patterns. In contrast, exam-oriented profiles may display later first visits or tighter clustering around assessment weeks. This analysis established a conceptual bridge between entry timing and participation trajectory, which was further explored in subsequent predictive models.

Figure 5.58

Box Plot of Timing of First Visit by User Profile

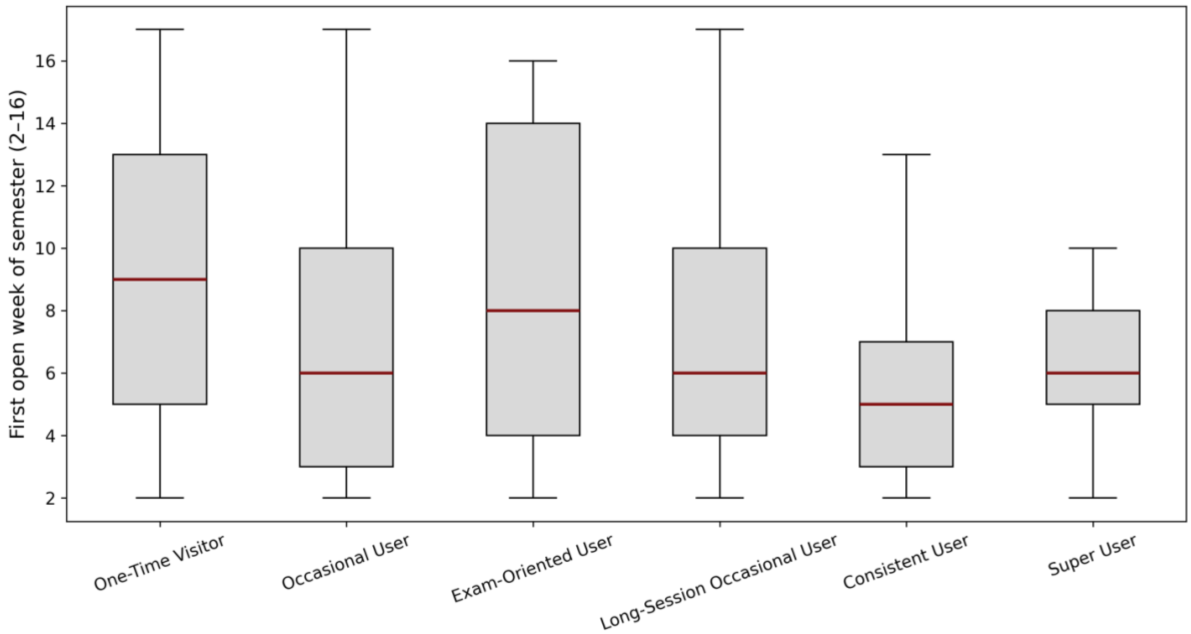
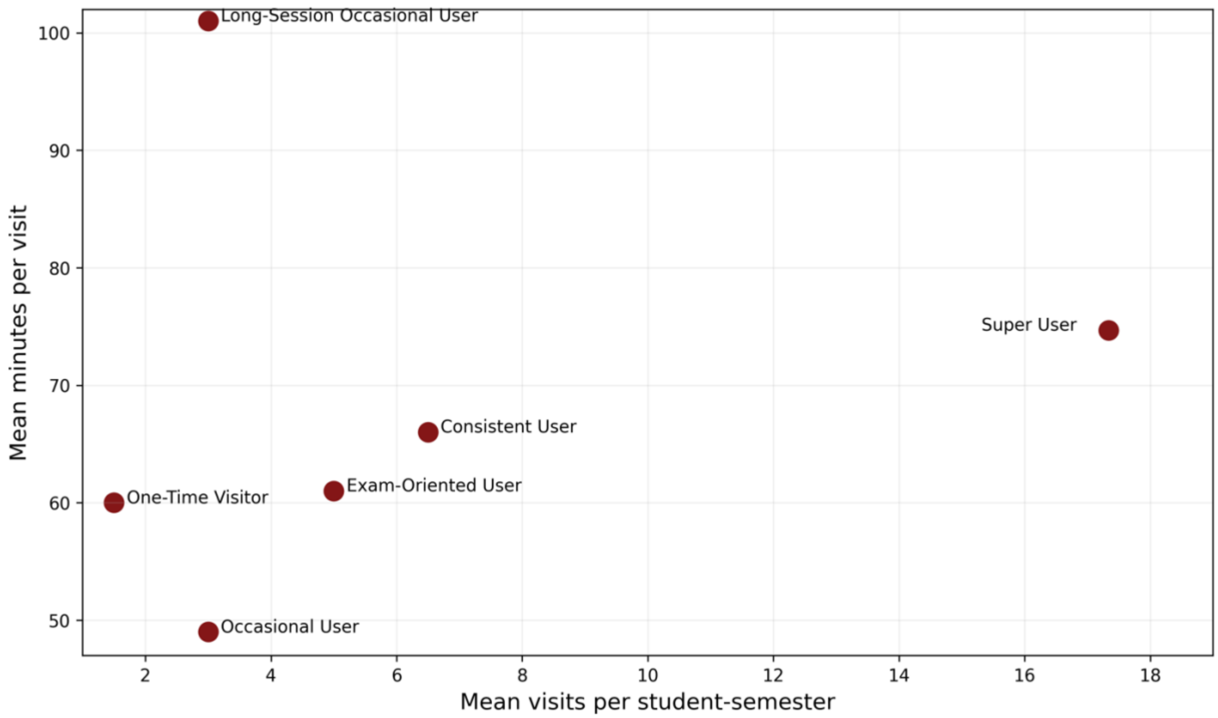


Figure 5.59 presents profile centroids along two dimensions: frequency (total visits) and session depth (mean number of minutes). This visualization clarifies that tutoring demand manifested along at least two distinct axes. Some students generated demand primarily through repeated visits, while others generated demand through longer sessions. These represent different forms of operational load. High frequency demand stresses scheduling and tutor availability. High depth demand often stresses tutor expertise and cognitive capacity.

Figure 5.59

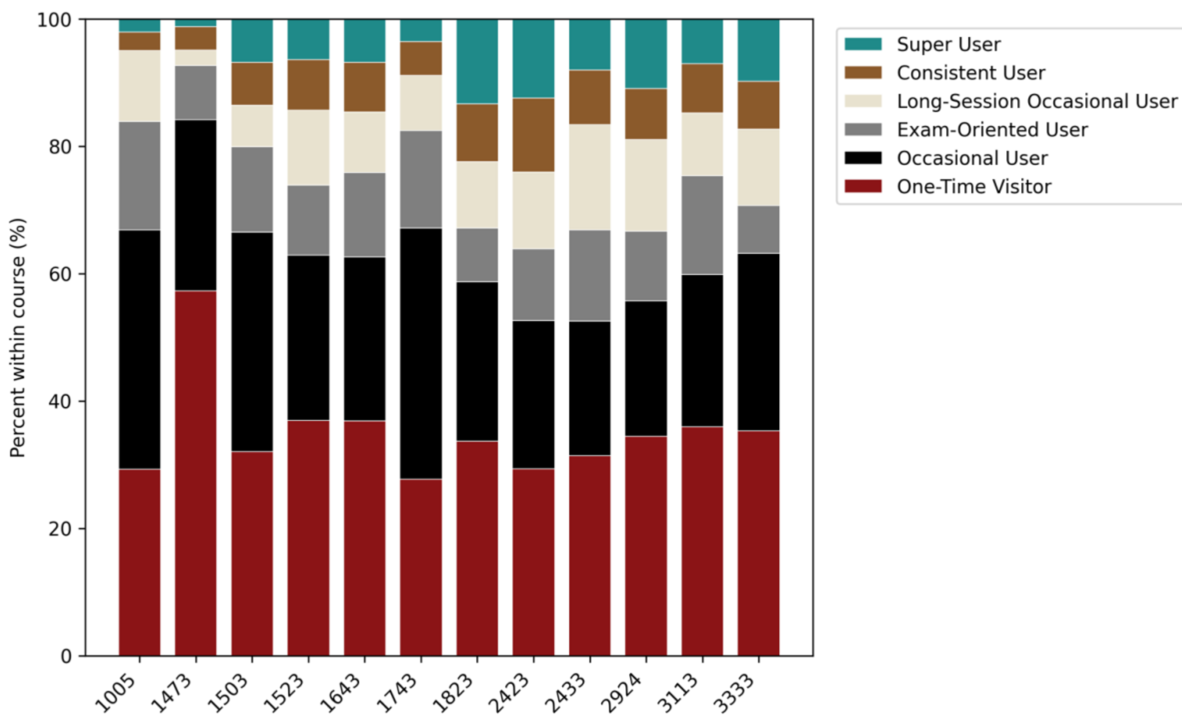
Scatter Plot of Profile Centroids: Frequency vs Session Depth



A final composition figure examined profile distribution within the highest volume courses. This chart provides department level actionability by identifying which major courses produced different types of engagement patterns. Courses generating higher proportions of sustained or high intensity profiles may represent curricular bottlenecks requiring integrated tutoring supports, structured review programming, or closer coordination with instructional faculty.

Figure 5.60

Stacked Bar Plot of Profile Composition in High-Volume Courses (Top 2 per Room)



A methodological clarification is warranted regarding the classification of exam-oriented users in this phase. Exam alignment was operationalized using an exam-week proxy (Weeks 4, 8, 12, and 15–16). This approach was intentional. The purpose was to identify broad patterns of student behavior specifically, whether students tended to concentrate their visits around typical assessment periods rather than to precisely match each visit to a specific coordinated exam date.

Because this analysis focused on developing behavioral profiles, the use of standardized exam-week windows provided a consistent and comparable framework across courses and semesters. Precise exam-date alignment was examined separately in earlier sections of the study, where course-level timing patterns were analyzed in detail. As such, the proxy approach used here prioritized consistency in classification over exact temporal precision.

A formal reclassification using exact coordinated exam calendars was not conducted within this phase of the analysis. However, given that exam timing was explicitly analyzed in prior sections and demonstrated clear clustering of visits around assessment periods, the proxy-based classification was considered sufficient for distinguishing exam-oriented behavior at the typological level. Future work could incorporate exact exam dates into the classification process to further validate and refine these behavioral categories.

Taken together, this section demonstrated that Math Center usage cannot be reduced to a simple high versus low continuum. Instead, it consists of qualitatively distinct participation modes: light touch engagement (one-time or occasional), repeated engagement (consistent or sustained), assessment-driven cyclical engagement (exam-oriented), and heavy demand driven by extreme frequency or long session intensity. These modes vary meaningfully by room band and semester, providing the empirical basis for student engagement interpretations and for the staffing and optimization models addressed in the fifth research question.

This profiling framework transformed attendance data from isolated visit counts into interpretable behavioral structures. It showed that the Math Center simultaneously functioned as an episodic support resource, an assessment-aligned preparation space, and a sustained supplemental learning environment, depending on the student–semester context. Importantly, this context inherently reflected the course in which the student was enrolled, as engagement patterns were shaped not only by individual behavior but also by course structure, assessment timing, and instructional demands.

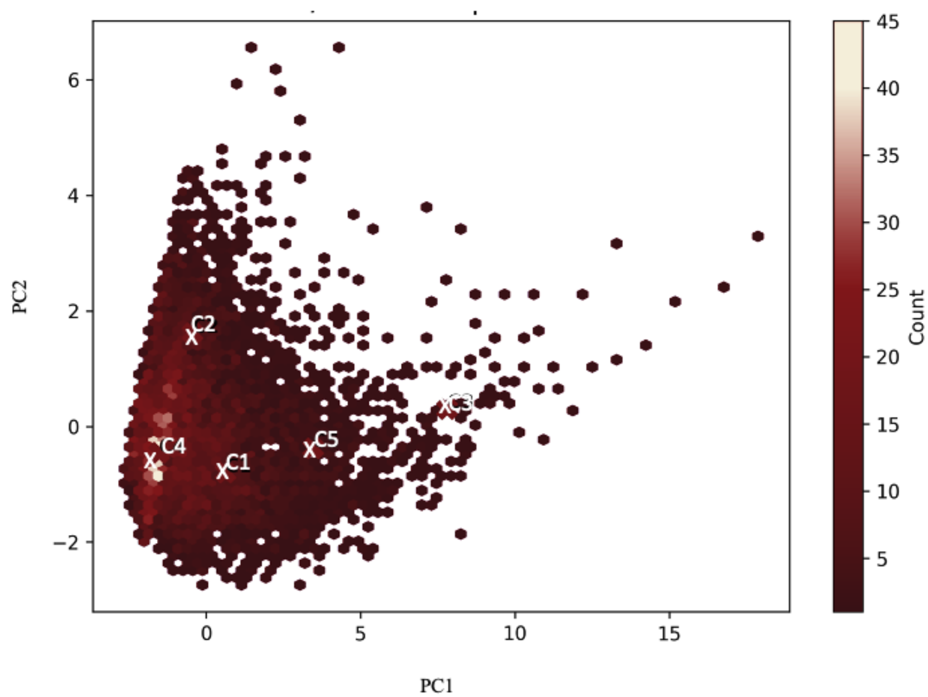
The next section addresses the core “distinct patterns” component of the third research question moving from descriptive summaries to a data-driven typology of student engagement. Earlier analyses established how often students attended within a semester and how that varied by course, room band, and timing of first visit. This section shifts the focus from isolated behavioral measures to integrated engagement profiles.

The unit of analysis remains the student-semester. This is critical conceptually; tutoring engagement was not a fixed, individual trait. A student might exhibit sustained engagement in one semester and exam-focused behavior in another, depending on course demands, assessment structures, and academic context. Treating each semester independently allows engagement to be interpreted as context-dependent behavior rather than stable disposition.

To detect meaningful engagement patterns without imposing arbitrary cutoffs, student–semesters were clustered using variables representing three core dimensions of engagement. Frequency was operationalized using total visits and visits per active week. Temporal persistence was captured through the number of distinct weeks active and the span of weeks from first to last visit. Service intensity was measured using total minutes, mean minutes per visit, and minutes per active week. The first week of attendance was included as a timing anchor, given that the third research question explicitly examined how the timing of initial engagement corresponded to subsequent behavior.

Figure 5.61

Scatter Plot of PCA (Principal Component Analysis) Density of PC1 (Principal Component 1) and PC2 (Principal Component 2)

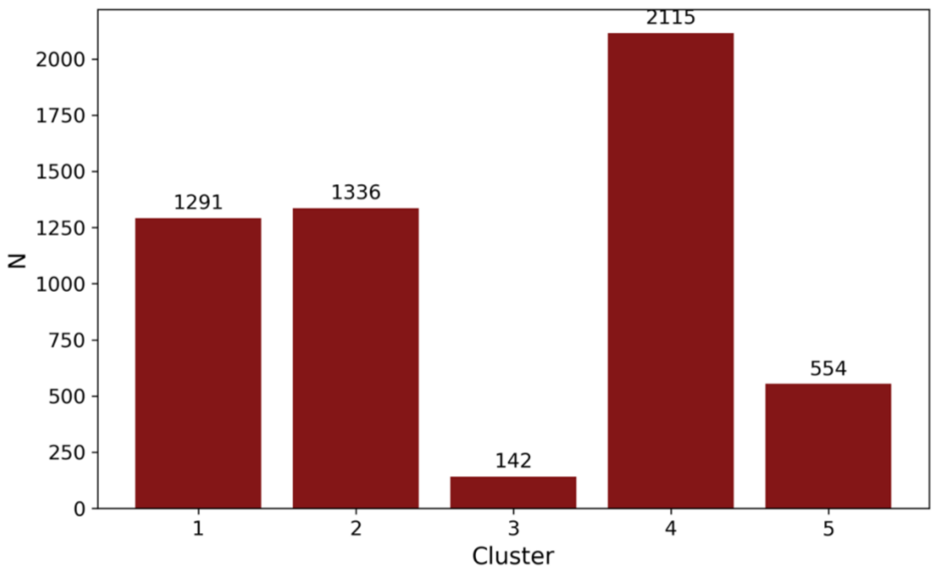


The PCA density visualization provides a two-dimensional projection of the multi-feature student-semester space. Dense regions reflect common behavioral patterns, typically lower frequency, and lower intensity engagement. Cluster centroids represent the center of each behavioral grouping. Visual separation of centroids supports the claim that engagement patterns are not purely continuous variation. Rather, there are distinguishable behavioral regions within the dataset. A silhouette validation check yielded a moderate value (approximately 0.28), which is typical in educational behavioral data. This indicates meaningful, but not perfectly separable, structure appropriate for constructing actionable typologies rather than rigid classifications.

Cluster-size distribution quantified the proportion of student semesters belonging to each engagement profile. This was essential for administrative interpretation because it contextualized how prevalent each participation style is. Typically, one large cluster reflects minimal engagement, while smaller clusters represent sustained, high-intensity, or timing-driven behaviors. Reporting the distribution prevents overemphasis on rare but visually salient patterns.

Figure 5.62

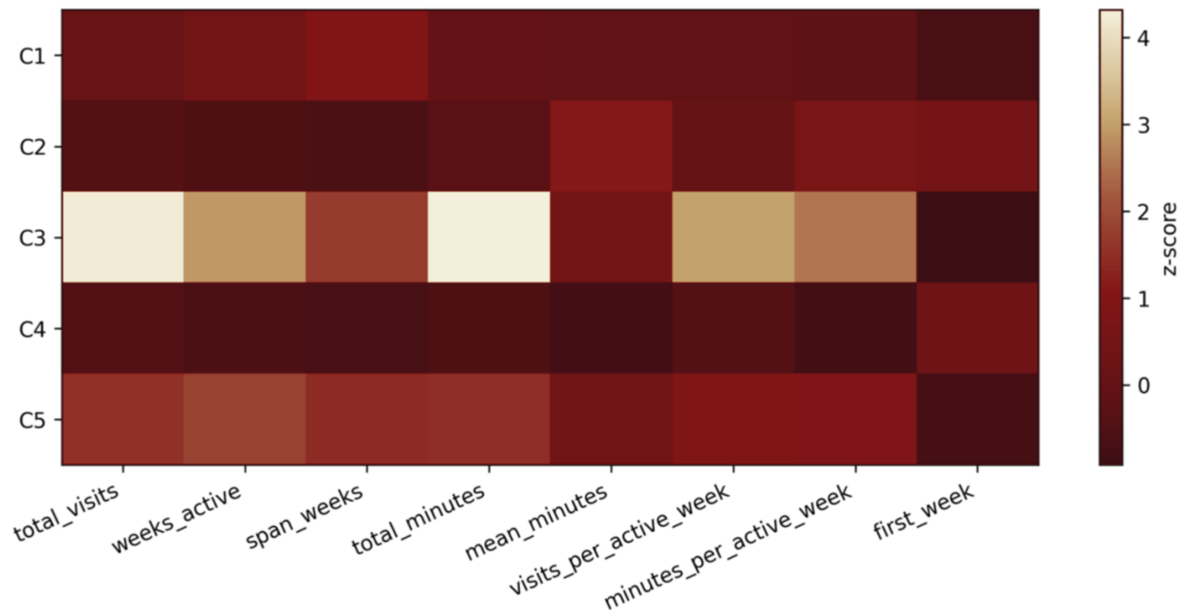
Bar Chart of the Cluster Sizes



The cluster signature heatmap is the primary interpretive tool. Each cluster is summarized across standardized engagement features, allowing direct comparison of behavioral emphasis. This enables assignment of academically interpretable profile names grounded in observed structure rather than intuition.

Figure 5.63

Heat Map of Cluster Signatures



Based on the clustering results, the five engagement profiles were best labeled as follows:

Minimal Engagement Users

These students exhibited very low total visits, minimal weeks active, limited span across the semester, and low total minutes. Their interaction with the Math Center was brief and random.

Exam-Oriented Users

These students demonstrated temporally concentrated engagement. Visits were concentrated within a small number of weeks, often later in the semester. Their pattern aligned with assessment-driven participation rather than sustained engagement.

Quick-Question Users

These students showed moderate to high visit counts but relatively low mean session durations. Their demand was driven by frequency rather than length, suggesting brief conceptual clarification rather than extended tutoring.

Consistent Users

These students engaged across many distinct weeks, with moderate visit frequency and broad temporal spread. Their pattern reflected habitual or routinized engagement with the Math Center.

Super Users

These students exhibited high visit counts, high total minutes, and sustained engagement across multiple weeks. They represented the highest-intensity demand group in both frequency and duration dimensions.

These labels aligned directly with the underlying engagement dimensions, frequency, persistence, duration, and timing while remaining academically neutral and operationally interpretable. Additionally, it looks like the same user groups that we had upon our analysis with no distinction for the long session occasional users. This was missed in the PCA analysis, but the analysis confirms the buckets we created upon observation of the data. Thus, we confirmed through data analytics our observations of the data are correct.

Subsequent visualizations examined how profile composition varied by semester, by dominant room band, and by timing of first visit. Variation across semesters indicated whether cohort-level or structural changes influenced engagement composition. Differences across room bands connected individual patterns to course structures, demonstrating that engagement styles concentrated within certain curricular groupings. Composition by timing of first visit addressed whether early entry predicted sustained engagement or whether late entry aligned more strongly with exam-driven behavior.

Figure 5.64

Stacked Bar Chart of Cluster Composition by Semester

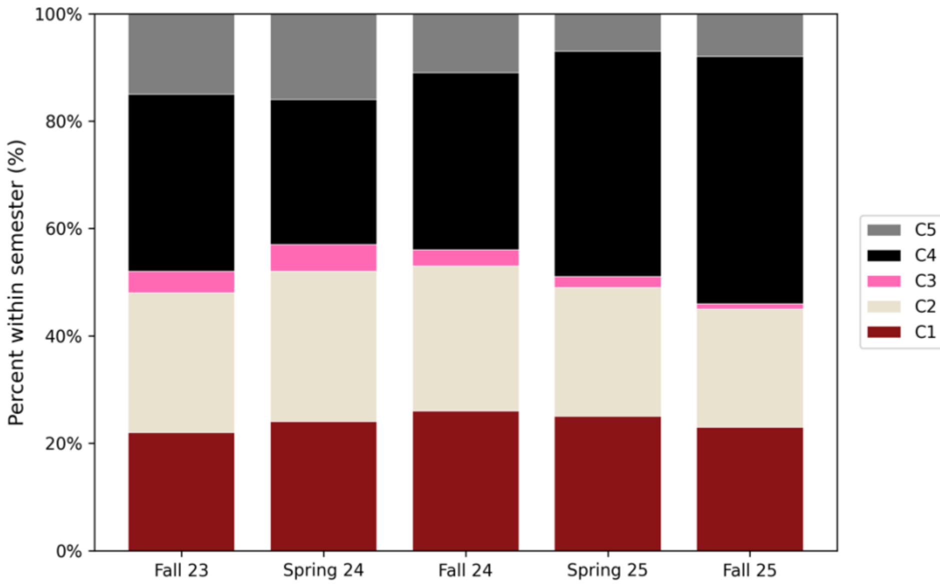


Figure 5.65

Stacked Bar Chart of Cluster Composition by Dominant Room

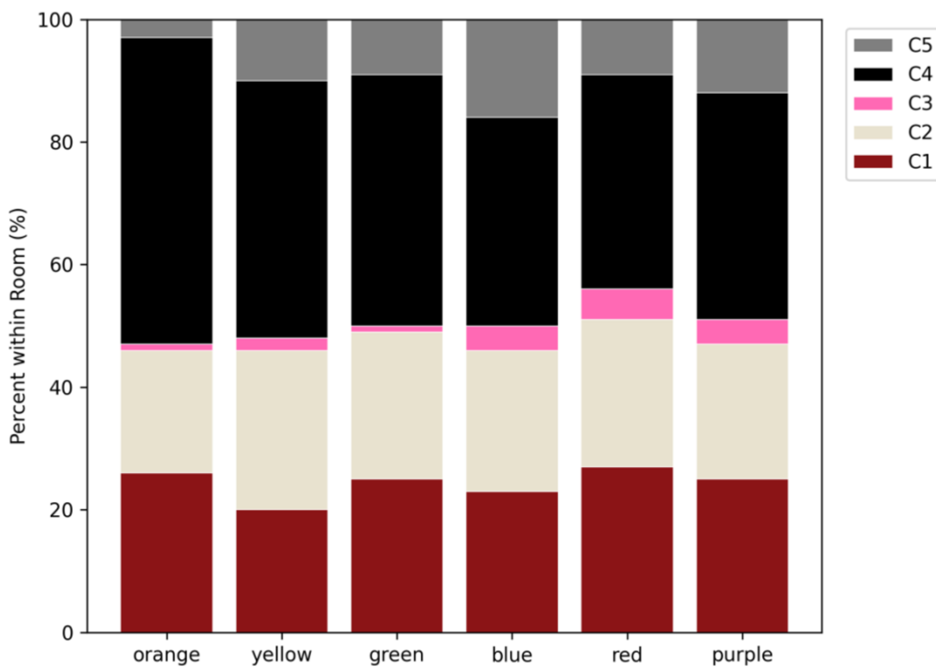
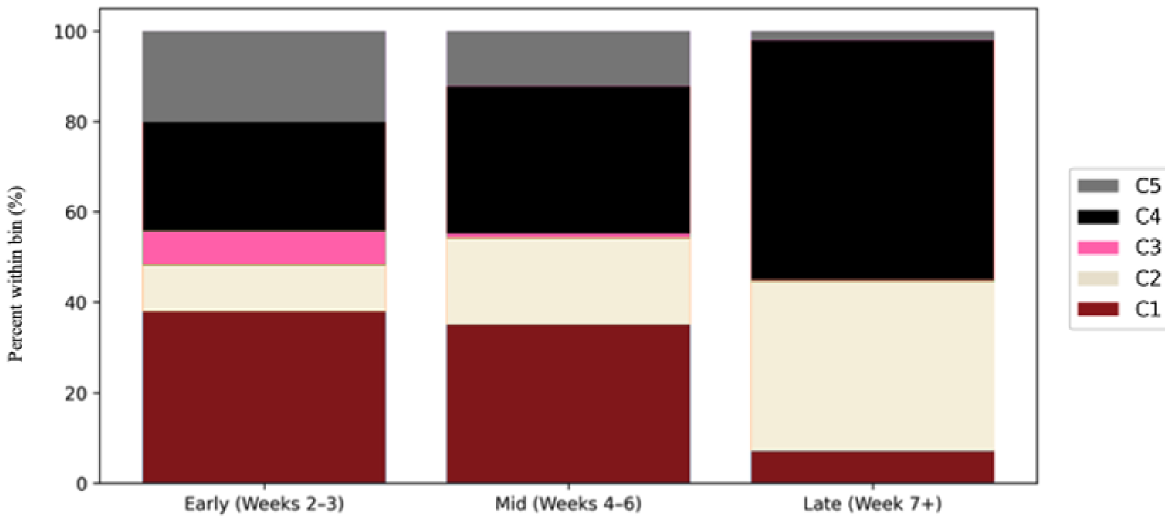


Figure 5.66

Stacked Bar Chart of Cluster Composition by Timing of First Visit

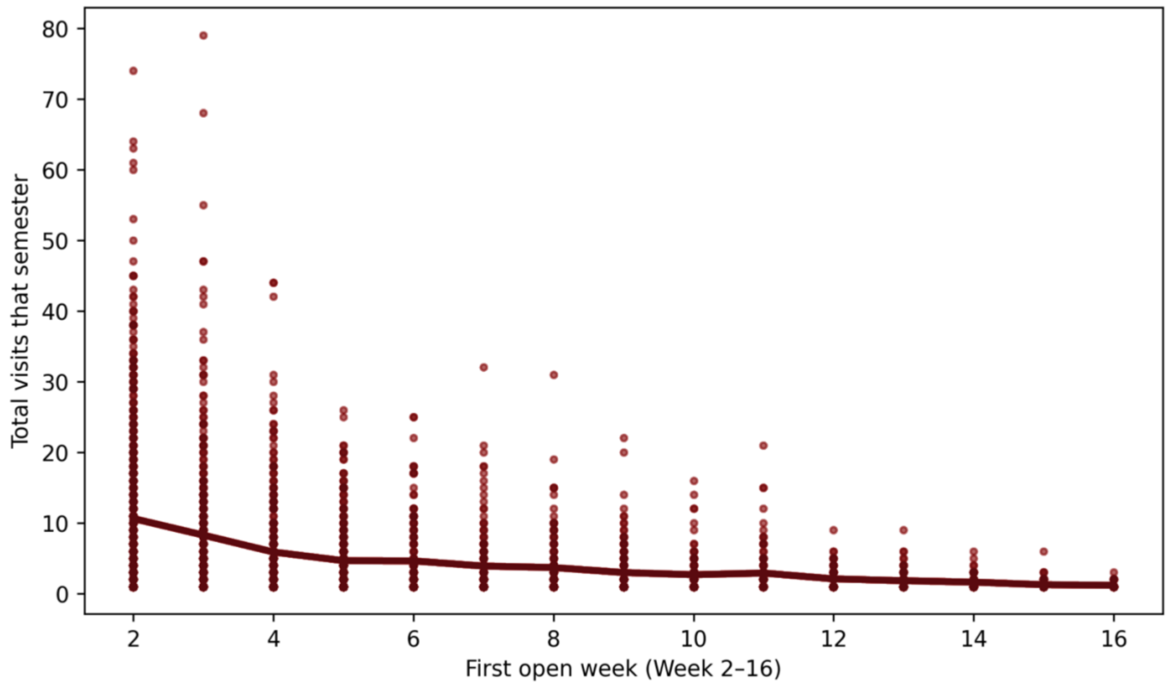


Collectively, this section demonstrates that Math Center demand is not unified. Engagement took on multiple, recurring forms that differed in frequency, temporal persistence, and service duration. These forms were distributed unevenly across course contexts and entry timing, providing the empirical foundation for both theoretical interpretation and staffing implications in later sections.

The final component of this section examined the relationship between initial engagement and subsequent attendance within the same semester. A central sub-question of the third research question considered whether the timing of a student's first visit corresponded to later engagement intensity. Using the Math Center open-week index (namely, it operated during Weeks 2–16 of each semester), students were grouped according to the week of their first visit, and then total semester visits were examined across these timing buckets.

Figure 5.67

Scatter Plot of First-Visit Week and Subsequent Usage

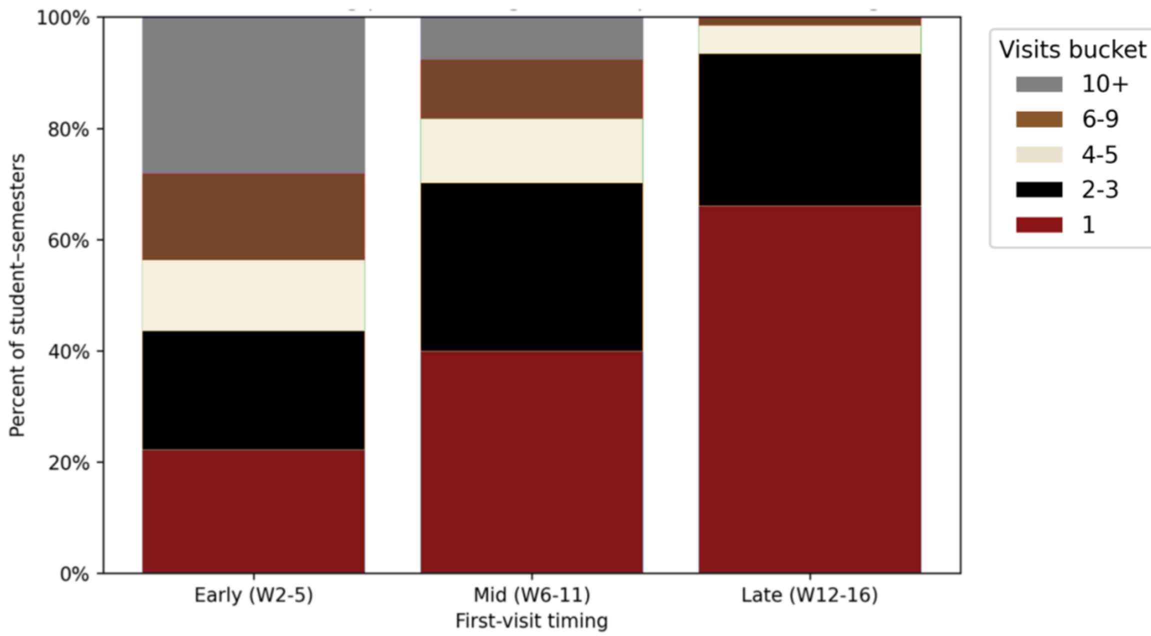


The resulting visualization demonstrated a clear temporal gradient; students who initiated Math Center use in the early weeks of the semester were more likely to accumulate additional visits in later weeks. Students whose first visit occurred in Weeks 2–5 were disproportionately represented in higher-usage categories. In contrast, students whose first visit occurred in Weeks 12–16 were concentrated in one-time or low-frequency usage buckets. This pattern indicates that entry timing is not neutral. It is systematically associated with subsequent engagement behavior.

Substantively, this finding provided a mechanism-relevant lens on engagement. Early entrants may be building structured academic routines that incorporated tutoring as a regular support practice. Alternatively, early entry may signal students experiencing sustained academic challenges who continued to seek assistance across multiple weeks. In either case, the early timing of first contact appears to be associated with greater persistence in attendance.

Figure 5.68

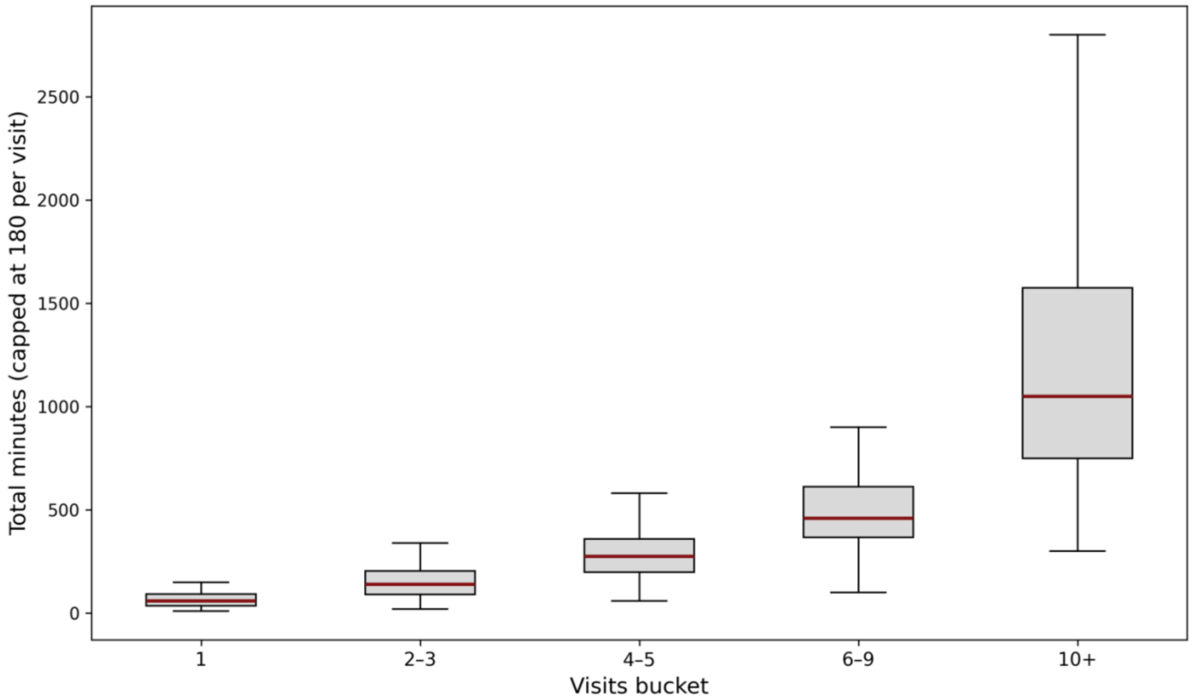
Stacked Bar Plot of First-Visit Timing Predicts Usage Bucket (Percent within Timing Bin)



Visit counts alone, however, do not fully capture the depth of engagement. To incorporate duration, total minutes per student semester were examined across usage buckets. Because each visit was capped at 180 minutes and evening sessions were excluded in the baseline dataset, total minutes reflect meaningful variation in frequency and sustained participation rather than extreme outliers. As expected, higher visit frequency buckets corresponded to substantially greater cumulative minutes. Students who visited more often also accumulated significantly more time within the tutoring environment, reinforcing the interpretation that sustained users represented deeper forms of engagement rather than repeated brief contact alone.

Figure 5.69

Box Plot of Total Minutes per Student-Semester by Usage Bucket



Taken together, these analyses demonstrate that engagement timing, frequency, and duration were interrelated. Early first visits were associated with higher visit counts and greater cumulative time investment, while late first visits tended to align with episodic or assessment-driven engagement.

Student-semester usage functions as a behavioral trace of participation in institutional mathematical support. Low frequency usage may reflect reactive engagement tied to a specific assessment or moment of difficulty. In contrast, sustained patterns characterized by early entry, repeated visits, and greater total minutes suggest ongoing participation in a support community. These distinctions extend beyond operational metrics. They represent different modes of engagement that may align with course structures, semester timing, and coordinated assessment rhythms identified in earlier analyses.

Early Attendance Impact Data

The fourth research question guiding this analysis was:

How does attendance at the Math Center during early coursework impact students' future Math Center attendance?

This question shifted the analytic focus from within-semester engagement (as considered in the third research question) to longitudinal continuation across semesters. It examines whether early engagement defined both temporally and positionally within the course sequence is associated with subsequent participation in later semesters.

Several sub-questions structured this analysis. First, what was the relationship between Math Center attendance in early coursework and the likelihood of continued attendance in subsequent semesters or academic years? Second, did students who utilized the Math Center during their first year of study demonstrate different engagement trajectories in later semesters compared to those who did not attend early? Third, how did the timing of first engagement within a semester relate to next semester return? Fourth, how did early engagement within the mathematics course progression pipeline correspond to later MLC participation?

The FA23 cohort serves as the entry cohort for this longitudinal analysis. It consists of all unique students who recorded at least one Math Center visit in the Fall 2023 semester under the baseline cleaning and scope rules used throughout this dissertation. These include administrative visits removed; recommended delete records removed; visit duration capped at 180 minutes; evening sessions excluded using a 17:30 cutoff; grey room and "Other" course records excluded; and Math Center open week indexing restricted to WeekOpen 2–16. Restricting to this consistent baseline ensured comparability with earlier research questions.

The fourth research question required two complementary definitions of "early." The first referred to early-semester engagement. Early-semester engagement was defined as a student's first Math Center visit occurring in WeekOpen 2–5. This operationalization captured students who sought support during the opening phase of the semester, prior to most coordinated midterm assessments.

The second definition referred to early course engagement within the mathematics progression sequence specified for this study. Course pipelines reflected structured progression in the OU mathematics curriculum for science, technology, engineering, or math majors: 1503→1523; 1523→ (1823 or 1914); 1823→(2423 or 2924); 2423→2433→2443; 2924→2934; and 2443/2934→any 3000-level course. In addition, 1643→1743 was treated as a separate early course sequence, and 1473 was treated as an entry point into subsequent coursework. Framing early engagement within these pipelines allowed analysis of whether MLC participation at foundational course stages corresponds to continued engagement as students advance.

Because the fourth research question centered on future attendance, the primary descriptive outcome in this section was next semester return, defined as whether a student in the FA23 cohort had any MLC visit in the immediately following semester. Figure 66 presents next semester return rates by dominant course in FA23 (where dominant course was the course with the most visits in that semester). This provides an initial course context view of persistence in Math Center engagement. Differences in return rates across dominant courses suggested that curricular context may influence whether students continue using the center.

Figure 5.70

Bar Chart of FA23 Cohort: Probability of Returning to MLC Next Semester, by Dominant Course (top courses)

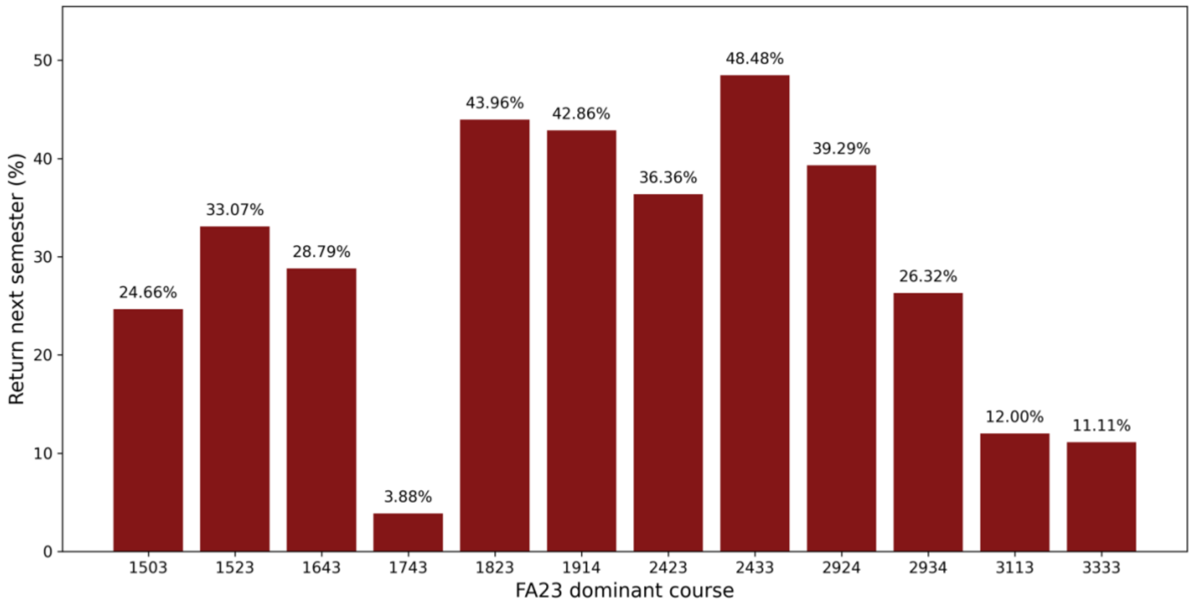
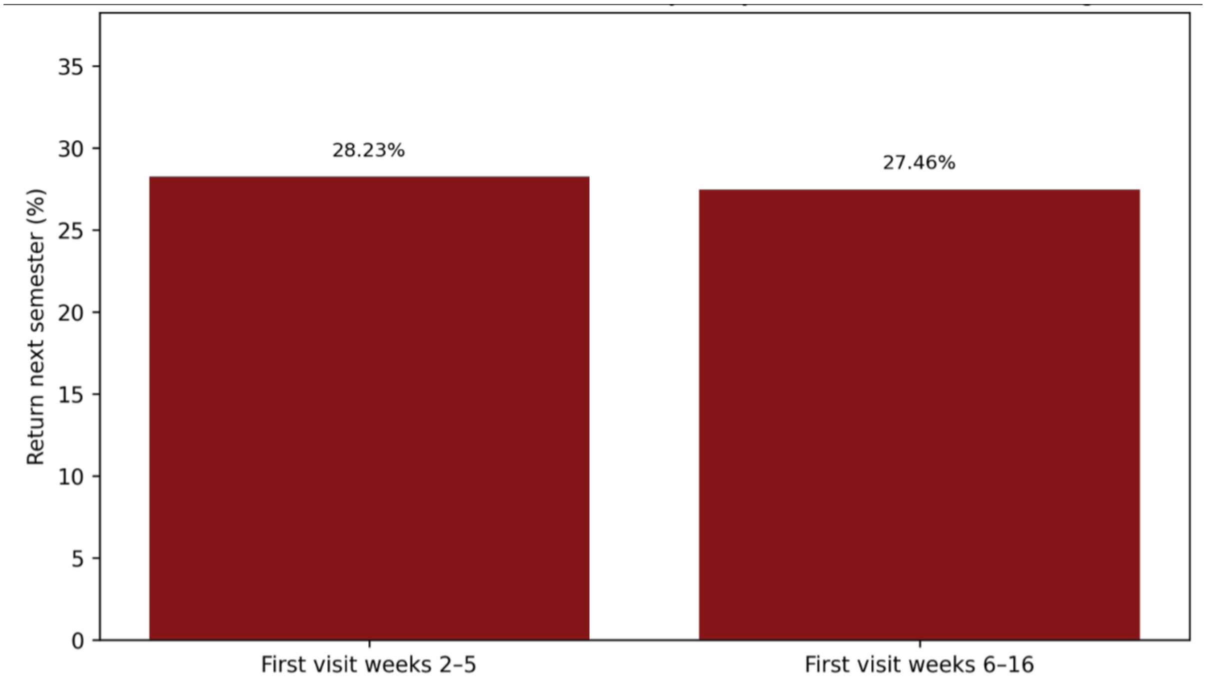


Figure 5.71 complements the course-level perspective by focusing on timing. Students whose first FA23 visit occurred early in the semester (WeekOpen 2–5) were compared to students whose first visit occurred later (WeekOpen 6–16). This directly tested the staffing-relevant hypothesis that early engagement (possibly reflecting proactive help-seeking or routine-building behavior) was associated with a higher probability of returning in the next semester.

Figure 5.71

Bar Chart of FA23 Cohort: Return Next Semester by Early-Semester First Visit Timing



Next semester's return captures short-horizon continuation, but the fourth research question explicitly addressed longer-term patterns across academic years. The cohort retention curve therefore tracks the proportion of the original FA23 cohort appearing in Math Center records in each subsequent semester. Although this descriptive curve did not isolate causal impact, it established the empirical baseline for longer run continuation and provided a target against which predictive models were evaluated in the next phase.

Course progression was central to interpreting these patterns. Figure 68 displays adjacent semester transitions in dominant course for the FA23 cohort as a threshold course flow network. Nodes in the figure represent dominant courses in sequential semesters, and directed edges represent observed student movement between courses. A "No MLC" node captures students who do not return in the subsequent semester to the Math Center. Conceptually, this Sankey-style visualization illustrates the flow of students across coursework and Math Center participation over time. In the subsequent modeling section, these transitions were operationalized analytically by estimating next-semester return as a function of early-semester and early course engagement.

Figure 5.72

Line Chart of FA23 Cohort: Continued Math Center Engagement Across Subsequent Semesters

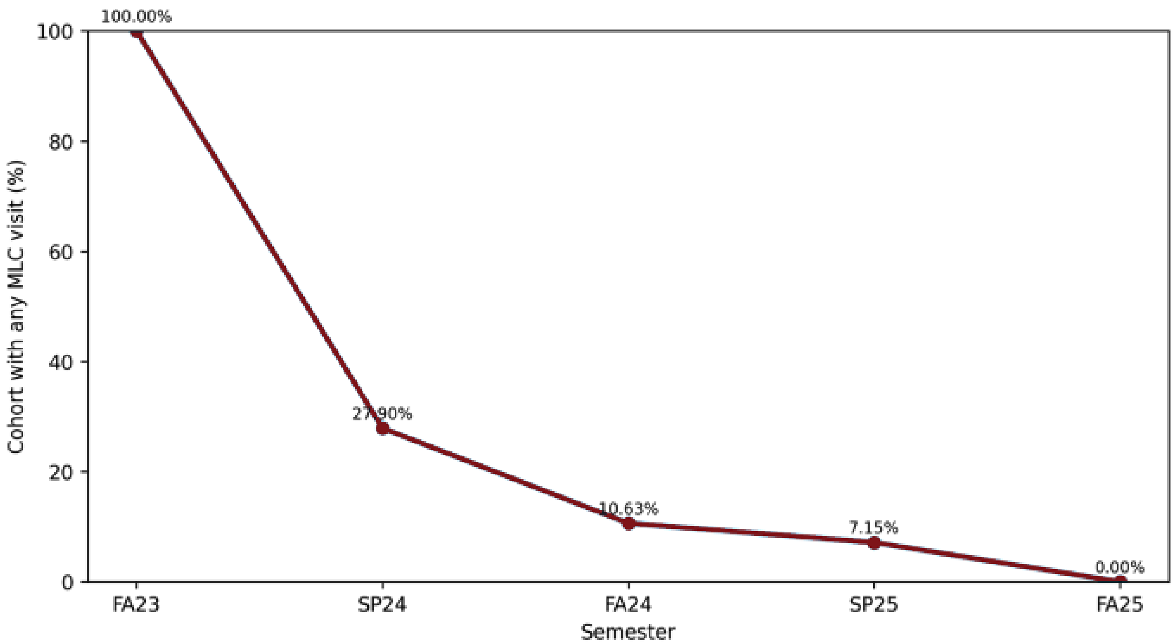
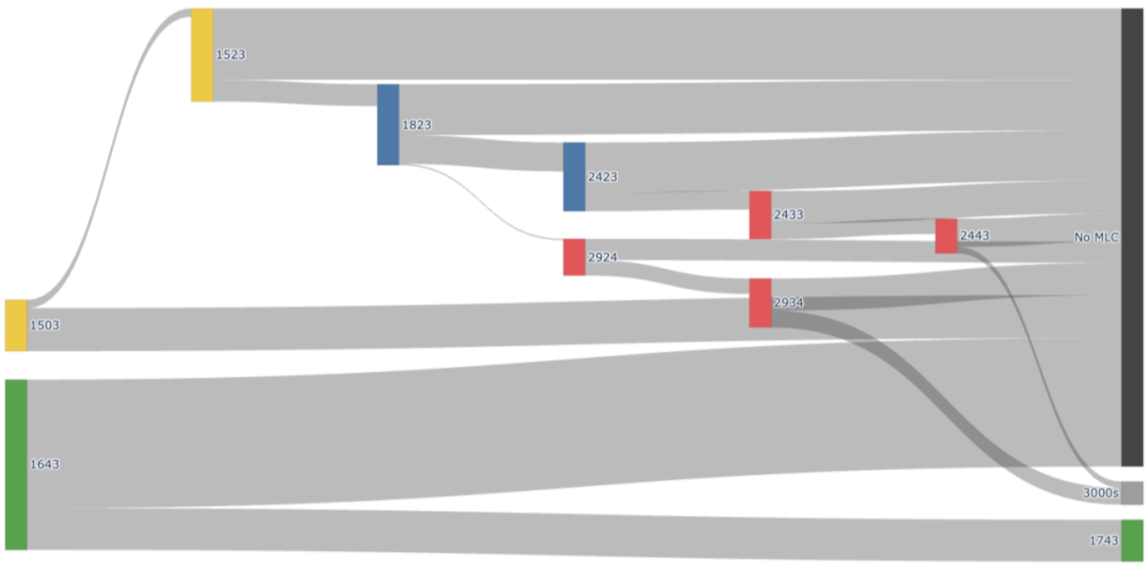


Figure 5.73

Sankey of Adjacent-Semester Course Progression



Participation in structured support environments such as the Math Center can be understood as a practice that develops over time. Help-seeking behaviors are shaped by course sequencing, assessment timing, and students' evolving identities as mathematics learners. The descriptive evidence presented here suggests that both course context and early-semester timing were associated with subsequent continuation. Students who engaged earlier in the semester and earlier in the course sequence appear more likely to re-engage in later terms. In the next phase of the fourth research question, these relationships are formalized using predictive models, including logistic regression and cohort-based transition analyses, to estimate the magnitude and uncertainty of early engagement effects.

The next section presents a formal estimation of the relationship between early Math Center engagement and continued attendance using a forward cohort design anchored in Fall 2023 (FA23). The primary outcome was next semester return, defined as whether a student recorded any MLC visit in the immediately following semester. The analytic dataset consisted of student-semester transitions beginning with the FA23 cohort and continuing across adjacent terms (FA23→SP24, SP24→FA24, FA24→SP25, SP25→FA25). This structure allowed repeated observations for the same student across transitions while maintaining a consistent forward-looking outcome definition.

The dependent variable, ReturnNext was coded as 1 if a student has at least one Math Center visit in the subsequent semester and 0 otherwise. Predictors were used to operationalize "early" engagement in two distinct ways. First, early-semester engagement was defined as a first visit occurring in WeekOpen 2–5, contrasted with later first visits (Weeks 6–16). Second, early-course engagement was represented through pipeline stage, based on the student's dominant course in the current semester and its position within the predefined mathematics progression sequence. These definitions aligned directly with the dual conceptualization of "early" introduced in the descriptive section.

Four logistic regression models were estimated to examine return behavior. Model specifications were constructed incrementally to assess the contribution of timing, engagement intensity, and course-sequence context. The final model included an interaction between early-semester engagement and visit frequency.

Figure 5.74 presents receiver operating characteristic (ROC) curves for each model, and the corresponding table reports the area under the curve (AUC) and Brier scores as measures of predictive discrimination and calibration. The ROC curve plots the tradeoff between the true positive rate (sensitivity) and false positive rate across different classification thresholds, providing a visual summary of a model's ability to distinguish between students who return and those who do not.

The AUC summarizes this curve into a single value ranging from 0.5 (no better than random chance) to 1.0 (perfect discrimination), with higher values indicating stronger ability to correctly differentiate outcomes. Improvements in AUC across specifications indicated the incremental explanatory contribution of intensity and pipeline variables.

The Brier score provided a complementary measure of predictive accuracy by quantifying the average squared difference between predicted probabilities and observed outcomes. Lower Brier scores indicate better calibration and overall prediction accuracy, reflecting how closely predicted return probabilities align with actual student behavior.

Figure 5.74

Line Graph of Predicting Next-Semester Return: ROC Curves (FA23 Cohort Panel)

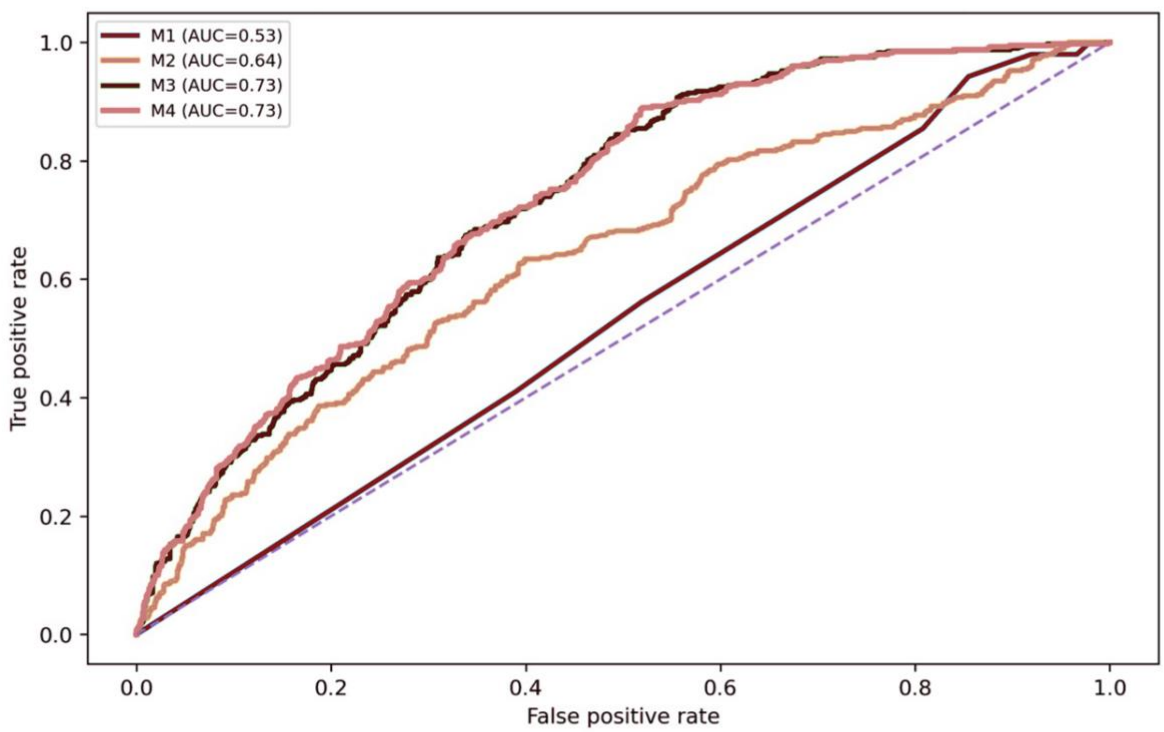


Table 5.3

Modeling Summaries

Model	AUC	Brier
M1 Timing-only	0.531	0.197
M2 +Intensity	0.639	0.189
M3 +Pipeline	0.731	0.172
M4 Interaction	0.735	0.171

Figure 5.75 displays predicted probabilities of next semester return derived from Model 4 across the range of visit intensity, contrasting early versus later first visits. These curves illustrated how early timing shifts continuation probability at different levels of engagement. If early entry increases predicted return at low to moderate visit levels, this suggested that timing exerted an independent association beyond simple intensity.

Figure 5.75

Line Graph of Predicted Probability of Returning next Semester by Early-Semester Timing and Visit Frequency

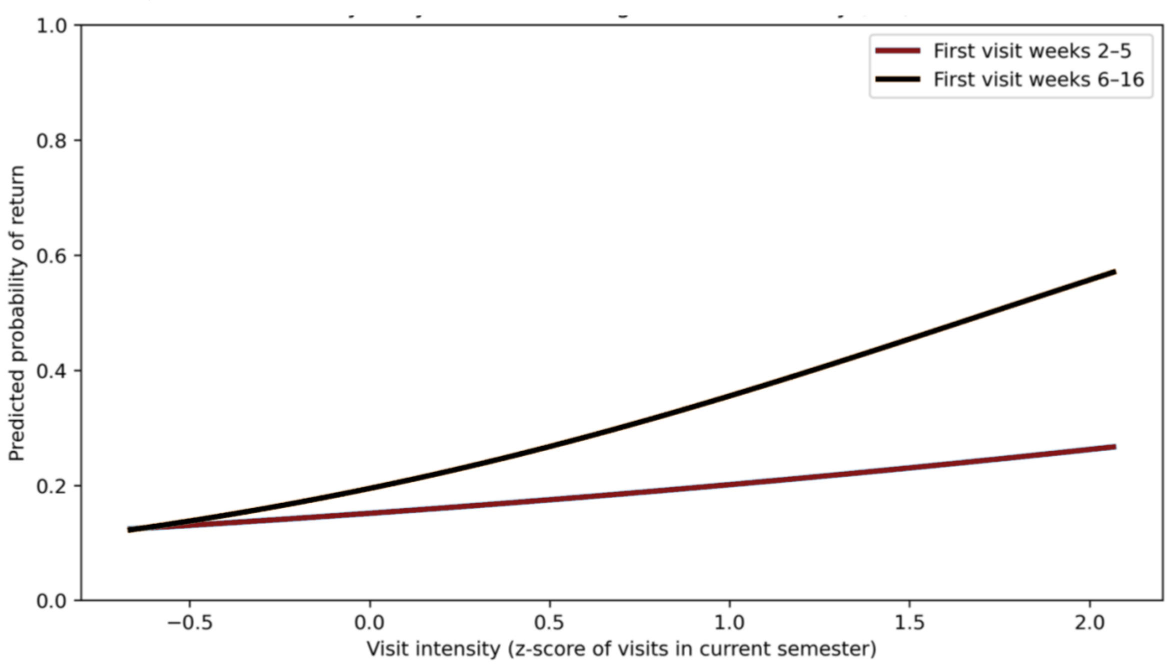
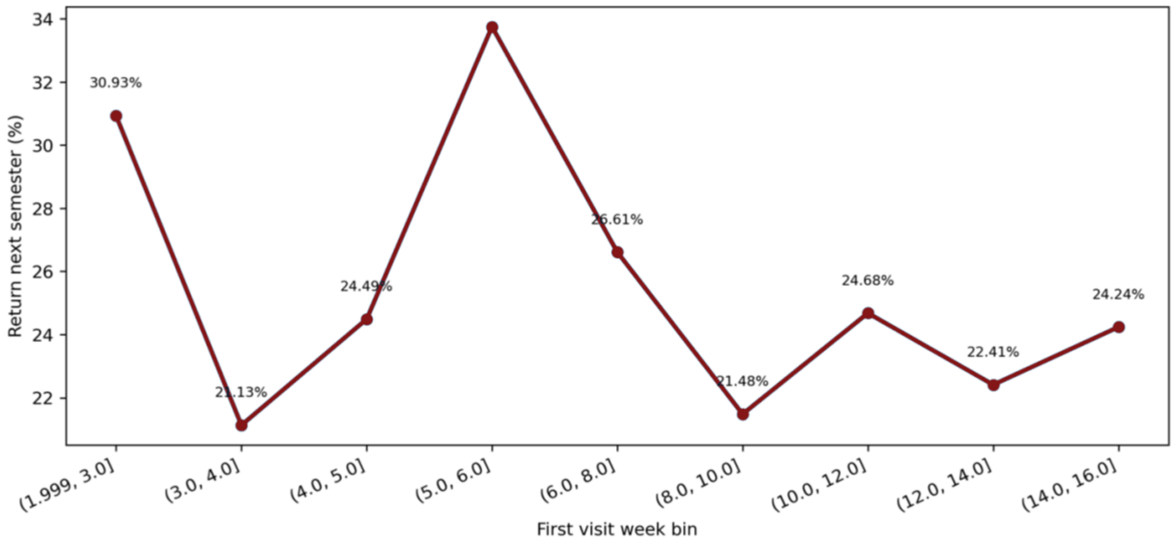


Figure 5.76 provides a model-free validation by plotting empirical return rates across binned first visit weeks. This descriptive check ensured that model-based inferences were consistent with observed continuation patterns.

Figure 5.76

Line Graph of Empirical Next-Semester Return Rate by First-Week Bin (FA23 Cohort Panel)



Continued Math Center attendance can be interpreted as sustained participation in a structured learning support practice. An early first visit (Weeks 2–5) plausibly reflected proactive help seeking, early awareness of institutional resources, or early academic challenge, each of which could increase the probability of continued engagement.

Administratively, the predicted probability curves translated statistical results into actionable guidance. Early-semester engagement appeared associated with higher continuation likelihood, supporting strategies that encourage earlier first visits through messaging, instructor coordination, and staffing alignment during Weeks 2–5.

Staffing and Service Optimization

The fifth research question guiding this analysis was:

> *What optimizations in staffing and services might be implemented based on student attendance patterns?*

This research question was explicitly application oriented. Whereas earlier research questions established how attendance is distributed across courses (first research question), when demand peaks and how it aligns with the academic calendar (second research question), how students differ in engagement style (third research question), and how early engagement relates to continued participation (fourth research question), the fifth research question synthesized these findings into concrete, evidence-based recommendations for staffing design and service delivery.

Three sub-questions guided this section. First, how did Math Center attendance differ between courses with coordinated structures and those without coordination? Second, based on observed attendance patterns and inferred student needs, were there identifiable times or approaches that optimize staffing of the Math Center? Third, could targeted outreach or structured interventions encourage greater utilization among specific student populations?

To address the first sub-question, the analysis leveraged the coordinated exam findings and course-level intensity metrics. Coordinated courses produce predictable, time-bound surges in demand that were visible in both weekday/hourly peak patterns and the event-time curves anchored around exam dates. In contrast, non-coordinated courses tended to generate demand that was either more diffuse or driven by local instructor pacing and assignment schedules. This distinction matters operationally because coordinated courses allow for proactive forecasting. Staffing might be increased in advance of known exam windows, tutor expertise might be concentrated in relevant rooms, and structured review programming might be scheduled during the observed lead time period (often one to two weekdays before an exam). Non-coordinated courses may instead benefit from flexible coverage models, generalist tutor deployment, and triage systems that can adapt to less predictable spikes.

The second sub-question focused on identifying optimal staffing times and deployment strategies. Across semesters, demand was temporally patterned rather than evenly distributed. At the center level, attendance concentrated midweek, with Wednesdays representing the largest share of visits and Fridays consistently the lowest. Within days, sign-ins and occupancy were concentrated in late morning through early afternoon, with consistent peaks around 10:00 a.m. and 1:00 p.m. Room-level analyses refined this further, showing that while most rooms share a 10:00 a.m.–2:00 p.m. pressure window, the precise peak days and peak hours vary by room band, reflecting course scheduling structures (e.g., Monday/Wednesday/Friday versus Tuesday/Thursday lecture patterns). These findings supported a staffing model that was differentiated along two axes: time-of-day staffing density (i.e., higher coverage during peak intake and peak occupancy windows) and room-specific staffing schedules aligned to weekday rhythms. In addition, the time-cost findings showed that staffing pressure was driven not only by arrivals but also by session duration and overlap. Rooms with longer average minutes per visit (e.g., the Purple Room) required deeper coverage and potentially more specialized tutoring expertise, even if arrival counts were lower than high volume gateway rooms.

These results support a hybrid staffing approach. High volume gateway rooms require throughput capacity and queue management during predictable peak hours. Advanced course rooms require fewer tutors overall but often need higher expertise density and longer coverage continuity due to time-intensive sessions. Exam window weeks require temporary surge staffing that is scheduled based on empirically identified lead times, rather than relying solely on exam dates themselves. Finally, because weekly demand oscillates with recurring peaks, staffing should be dynamic across open weeks, scaling up during predictable surge periods and reallocating resources during low-demand weeks to training, outreach, or structured programming.

The third sub-question considered whether targeted outreach or interventions could increase Math Center utilization among specific populations. Findings from the third and fourth research questions indicated that timing of first engagement matters: students who initiated tutoring early in the semester were more likely to become sustained users and to return in subsequent semesters. This provided a strong rationale for early-semester interventions aimed at increasing first time visits, particularly during Weeks 2–5. Such interventions might include targeted messaging in early course sections, instructor driven referrals aligned to the first major assessment cycle, brief "first visit" orientation structures to reduce friction, and proactive reminders timed to known midweek and midday attendance windows. The user profile framework further suggested that different populations required different strategies. Exam aligned users might respond best to calendar-linked outreach and structured review sessions. Minimal-engagement students may benefit from low barrier entry points (e.g., quick diagnostic help, short workshops). Sustained and high intensity users may benefit from continuity strategies, such as stable tutor assignment by course band, dedicated exam prep blocks, or small group supports that reduce individual tutoring load while maintaining quality.

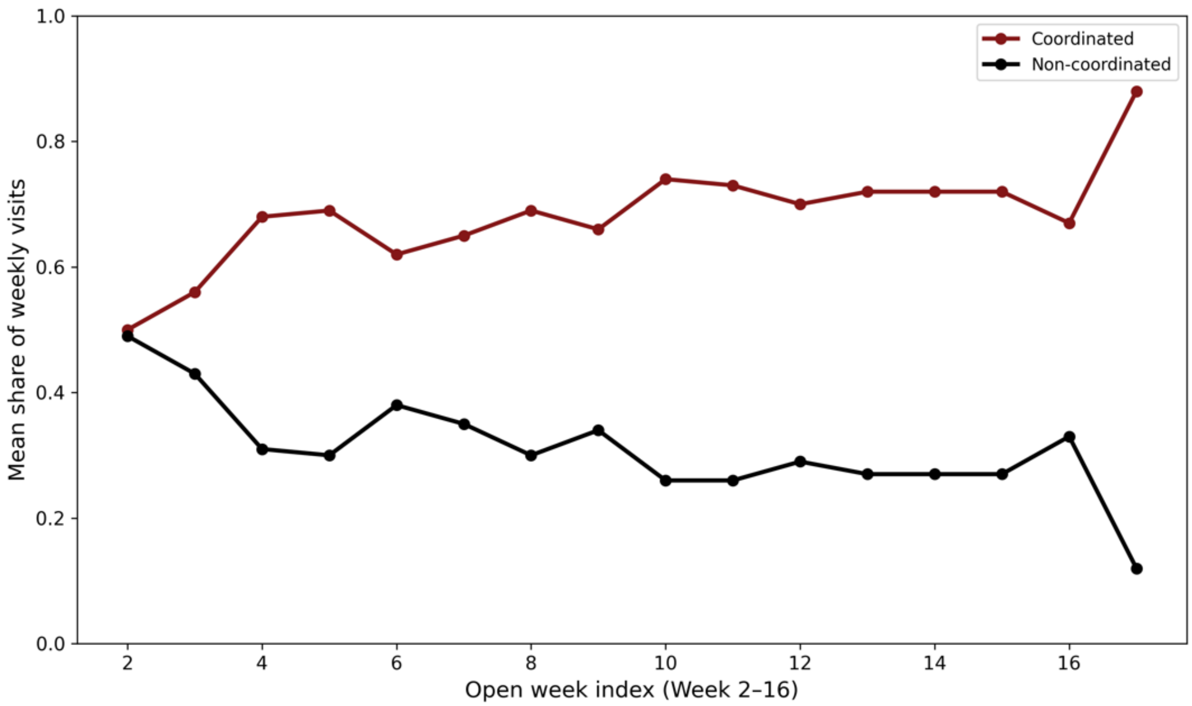
Taken together, the fifth research question translated the empirical findings into actionable optimization levers. Coordinated course demand supports forecasted surge staffing and structured exam cycle programming. Temporal patterns support differential staffing by weekday, hour, and room band rather than uniform coverage. Student-level findings support early-semester outreach designed to increase first time engagement and improve continuation. In combination, these recommendations frame optimization not as a single staffing increase, but as a targeted alignment of tutor capacity, expertise, scheduling, and outreach with the demonstrated structure of student demand.

To inform staffing optimization, visits were partitioned into coordinated and non-coordinated course groups. Coordinated courses include 1503/1523, 1643, 1743, 1823, and 1914; all other included courses were classified as non-coordinated. This distinction reflected structural differences in assessment design and pacing. Coordinated courses follow shared exam calendars and common assessment structures, whereas non-coordinated courses vary more substantially across instructors and sections.

Figure 5.77 presents the mean share of weekly visits attributable to coordinated versus non-coordinated courses, pooled across semesters (WeekOpen 2–16). This figure provides a proportional view of demand contribution. If coordinated courses consistently accounted for a substantial share of total visits, this indicates that assessment synchronization was a primary driver of Math Center traffic. Conversely, a more balanced distribution would suggest that demand was distributed more diffusely across the curriculum. Understanding this proportional structure was critical for forecasting because coordinated courses generate synchronized demand rather than isolated, section-level fluctuations.

Figure 5.77

Line Graph of Visits by Coordinated or Non-Coordinated Courses



Because staffing is deployed by room band rather than by individual course, weekly volatility was summarized at the room band level using the coefficient of variation (CV = standard deviation divided by mean) of weekly visit totals. The CV provided a normalized measure of demand variability across weeks. Higher CV values indicated less predictable weekly demand, while lower CV values reflected more stable and consistent usage patterns. Rooms with elevated volatility require more flexible staffing models capable of responding to surges, whereas rooms with lower volatility allow for more stable baseline staffing assignments.

For coordinated course groups, exam calendars permit event time alignment of tutoring demand. Daily visit counts were computed for offsets ranging from seven days before to two days after each exam (DayOffset −7 through +2) and averaged across exam instances and semesters. These aligned curves estimated the empirically observed lead time surge in tutoring demand associated with coordinated assessments. The resulting event-time profiles revealed not only whether demand increases near exam dates, but also when that increase began. Identifying the peak offset often one to two weekdays before the exam provided actionable insight into when staffing should be augmented to manage congestion and maintain service quality.

Figure 5.78

Bar Graph of Coefficient of Variation by Room Color

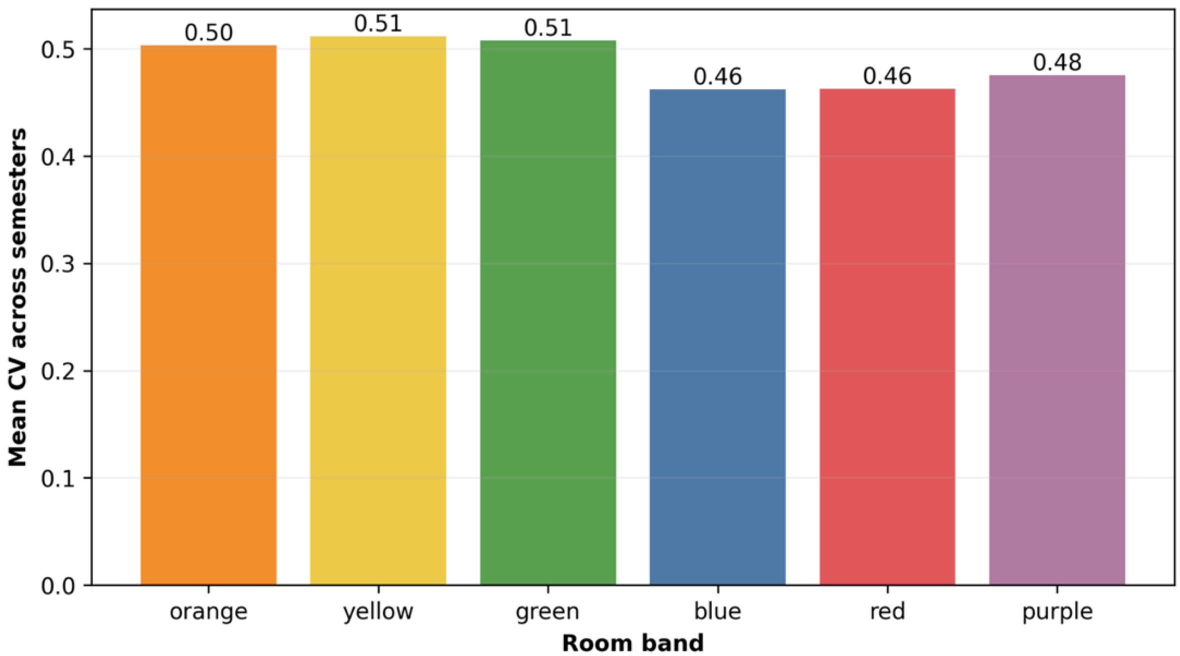
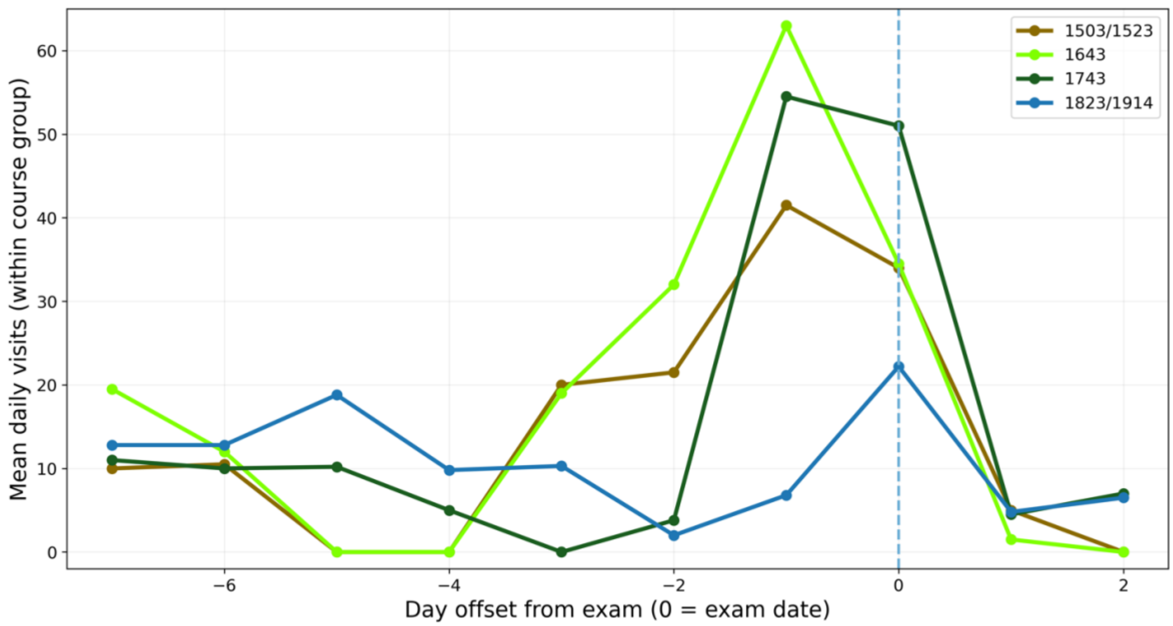


Figure 5.79

Line Graph of Demand based on Exam Window



Together, the proportional weekly shares, volatility metrics, and event time surge curves provide a multi-layered operational view of demand structure. Coordinated courses generated forecastable assessment driven surges, non-coordinated courses contribute baseline or locally variable demand, and room-level volatility quantifies predictability across weeks. These empirical patterns established the foundation for differentiated staffing models that align tutor allocation with both structural course characteristics and observed demand dynamics.

Hourly occupancy was computed by counting the number of tutoring sessions overlapping each hourly block (e.g., 10:00–11:00). Unlike arrival counts, which capture when students enter the Math Center, occupancy measures concurrent student load and therefore serves as a direct proxy for staffing pressure. Because tutoring sessions vary in duration and often overlap, occupancy provided a more accurate representation of real-time service demand than check-in volume alone.

To support practical staffing decisions, occupancy was summarized across all open days using percentile thresholds. Percentiles allowed the center to explicitly balance cost against the risk of overload. Rather than staffing to the absolute maximum observed occupancy, which may reflect rare surge conditions, percentile-based targets provided structured scenarios aligned with different tolerance levels for queue formation.

Three staffing scenarios were developed for each room band and hour block:

- Balanced staffing, based on the 90th percentile of observed occupancy (P90).
- Conservative staffing, based on the 95th percentile (P95).
- Surge ceiling staffing, based on the maximum observed occupancy.

Tutor requirements were calculated as the ceiling of occupancy divided by three, reflecting an operational assumption that one tutor can effectively manage up to three concurrent students. This conversion translated occupancy percentiles into concrete tutor counts.
Figure 5.80 presents the Balanced (P90) staffing requirements as daily curves by room band. These curves highlight when each band experiences peak staffing pressure. Because peaks vary by room band and hour, this visualization supports staggered scheduling and targeted allocation of tutor expertise. For example, if one band peaks from 10:00–12:00 while other peaks from 12:00–2:00, tutor shifts could be staggered to reduce idle time while maintaining coverage during peak overlap windows.

Figure 5.80

Heat Map of Required Tutors by Room and Hour (Balanced)

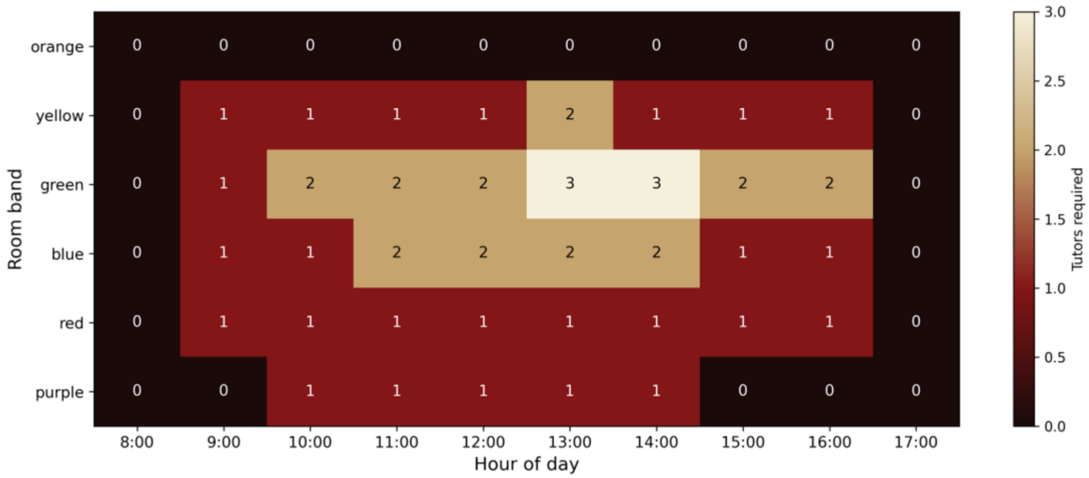


Figure 5.81

Heat Map of Required Tutors by Room and Hour (Conservative)

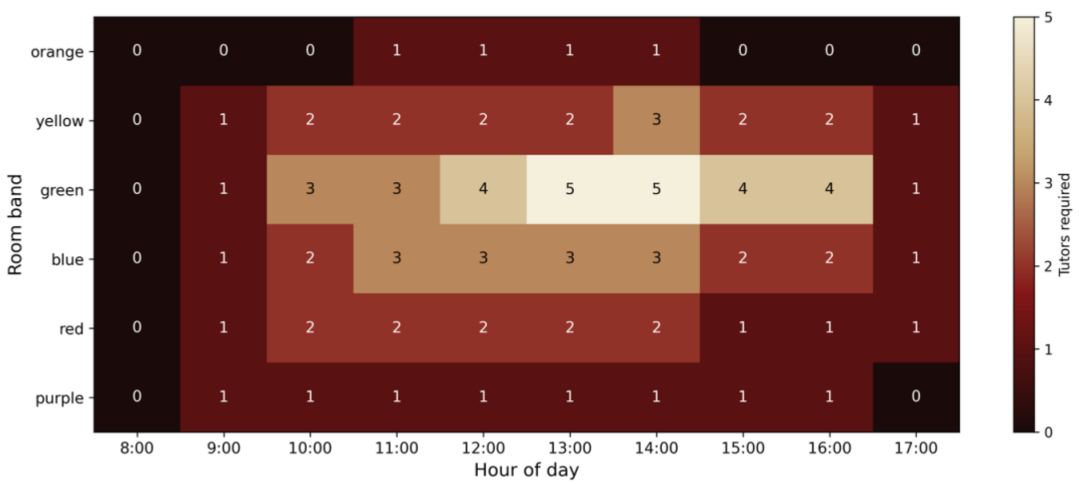


Figure 5.82

Heat Map of Required Tutors by Room and Hour (Max Tutors Required)

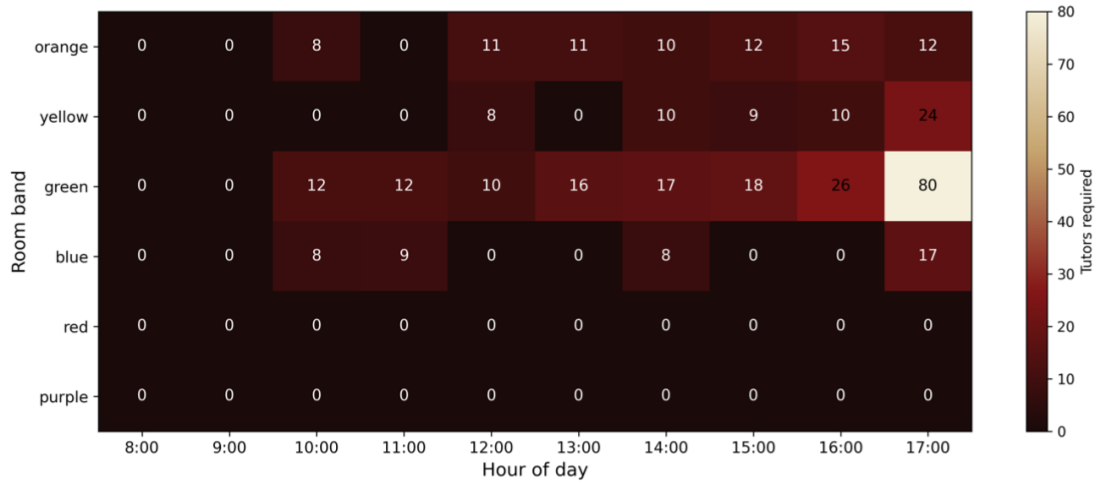
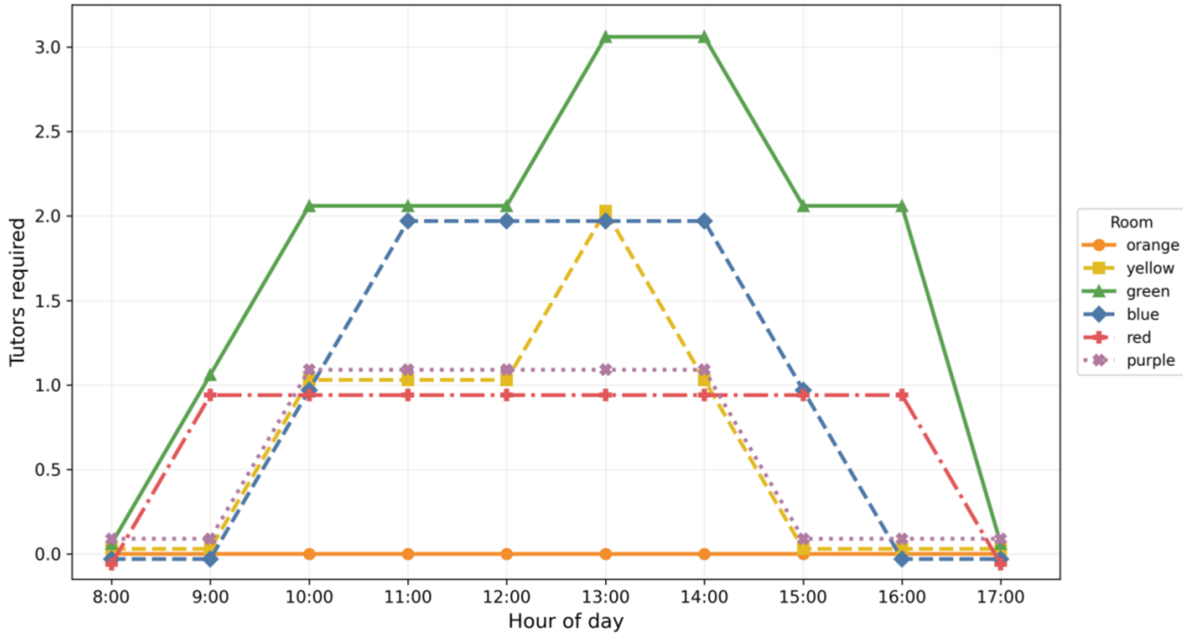


Figure 5.83 aggregates tutor requirements across room bands under the assumption that each band was staffed independently. The resulting curve represented total tutor demand by hour across the center and identified the campus-wide peak hour. This figure is particularly useful for setting upper bounds on scheduling capacity, anticipating space constraints, and aligning staffing budgets with empirically observed maximum load periods.

Figure 5.83

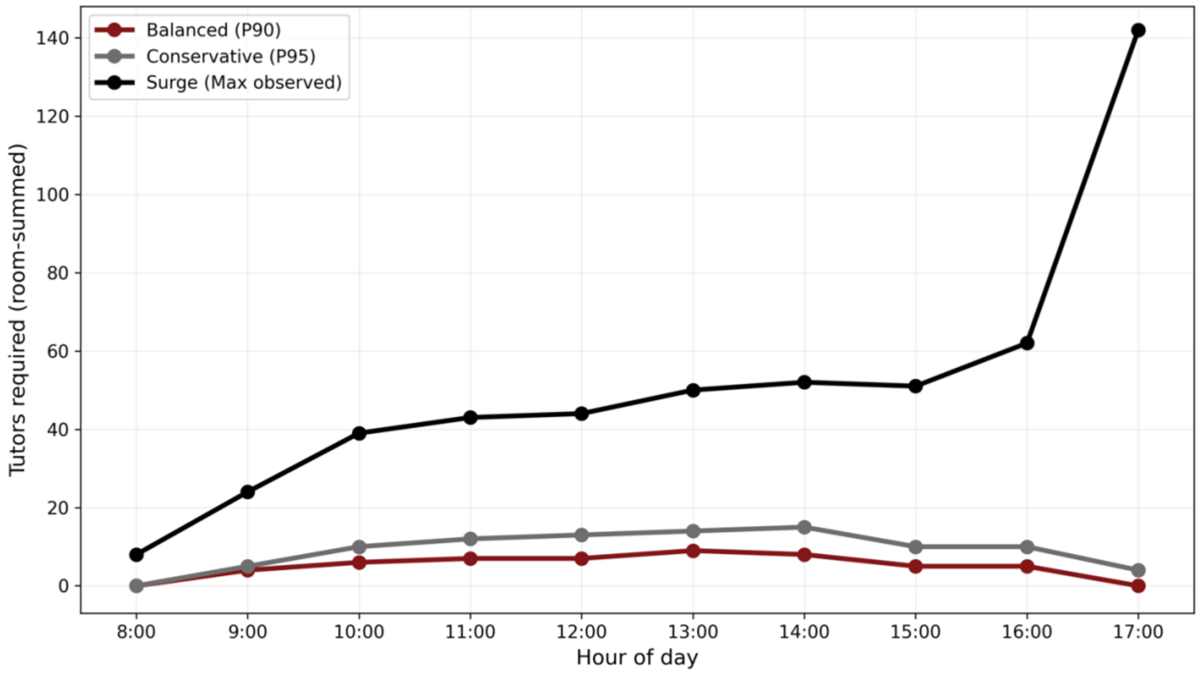
Line Graph of Required Tutors Across Hour of Day by Room



As a default operational recommendation, the Balanced (P90) scenario represented a practical compromise between cost efficiency and queue risk. Staffing at the 90th percentile covers typical high demand conditions without overcommitting resources to rare extremes. Rooms with consistently high occupancy or longer overlap windows, particularly those associated with coordinated courses or sustained engagement profiles, should receive stable baseline staffing coverage. Lower demand rooms may be covered through flexible strategies such as floating tutors, staggered shifts, or on call support during non-peak hours.

Figure 5.84

Line Graph of Tutor Demand



In the final synthesis, these occupancy-based staffing curves were integrated with exam-window surge analyses to produce a recommended schedule that accounts for both routine peak hours and predictable assessment driven spikes. Together, these optimization tools shifted staffing from reactive adjustment to data aligned deployment grounded in observed attendance structure.

The final analytic component evaluated the role of evening (referred to as “After Dark”) programming as a potential mechanism for increasing continued Math Center engagement. In this design, treated records were defined as student-semester observations with at least one After Dark visit. The first After Dark visit date served as the index date. Control observations consisted of student semesters with no After Dark visits. To reduce structural confounding, controls were matched and defined by semester, dominant room band, and first visit timing bin.

This matching structure aligned course context, calendar positioning, and baseline engagement timing, isolating exposure to After Dark participation rather than differences in opportunity or curricular structure.

Figure 5.85 compared same semester return rates between treated and matched control groups. This comparison assessed whether students who attend sessions were more likely to return for additional tutoring within the same semester. Because matching controls for semester, room context, and first-visit timing, differences in return rates were less likely to reflect simple course composition effects and more likely to reflect behavioral continuation associated with After Dark engagement.

Figure 5.85

Bar Graph of Same-Semester Return After Dark or No After Dark Visit

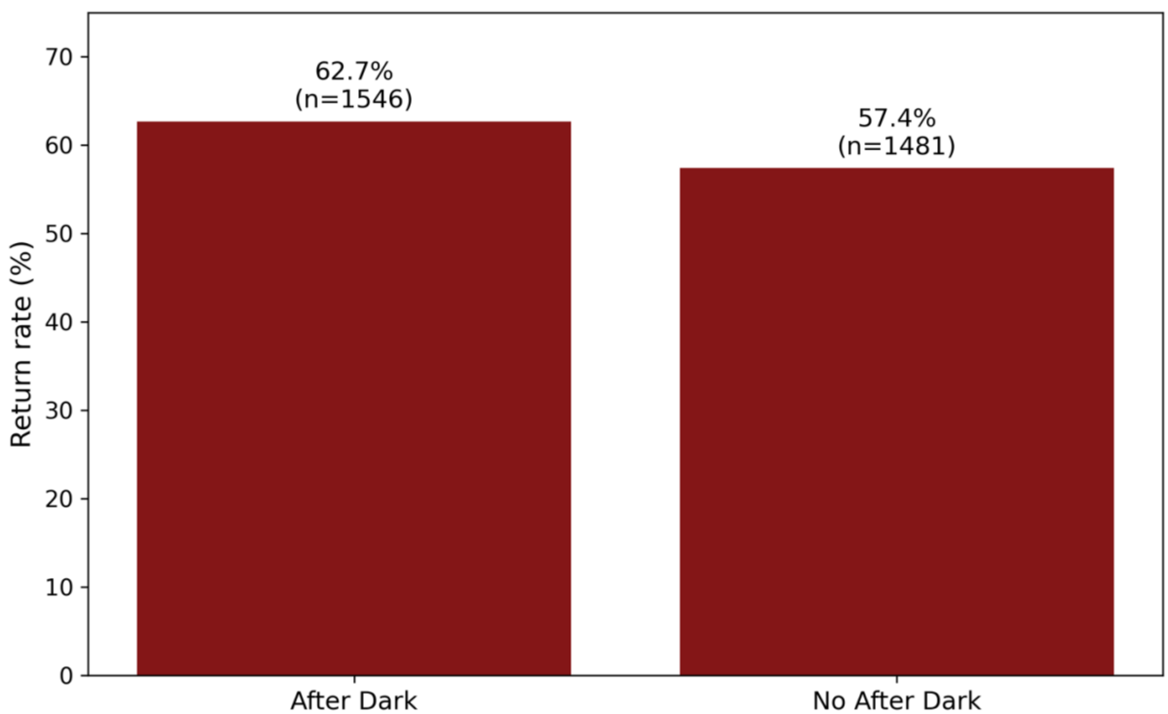
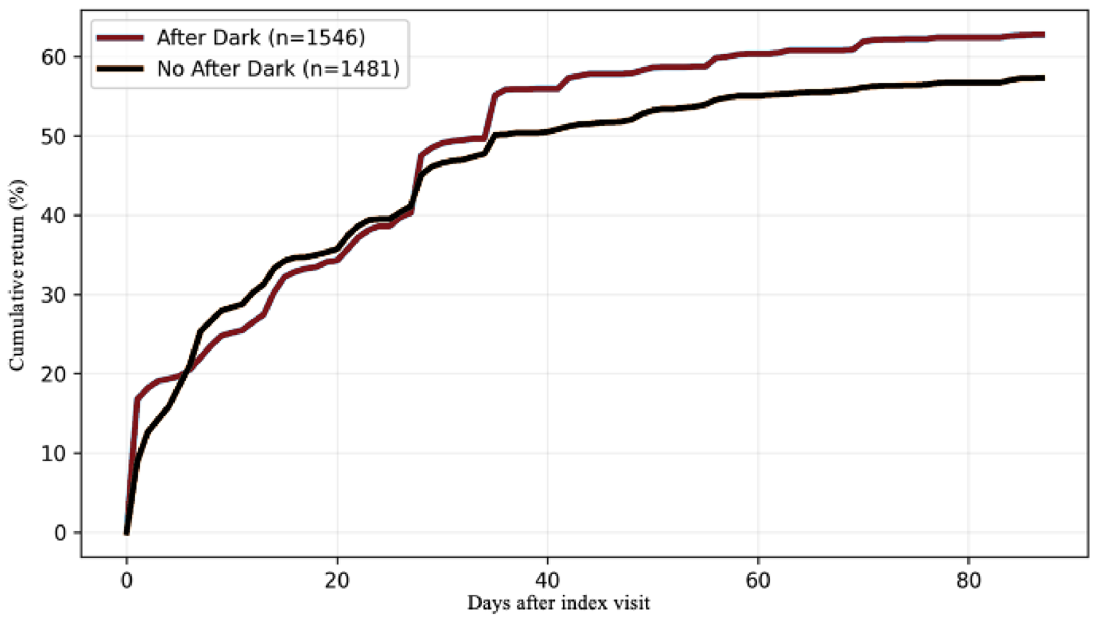


Figure 5.86 presents a cumulative return curve following the index date. This descriptive survival-style visualization showed how quickly students return to the Math Center after attending (or not attending) an After Dark session. Steeper curves indicated faster re-engagement. If students demonstrate both higher cumulative return and shorter time to return, this suggested that After Dark participation may function not only as a one-time event but also as a catalyst for subsequent student engagement with the Math Center.

Figure 5.86

Line Graph of Probability of Returning to the Math Center based on After Dark Visits



Substantively, After Dark programming differs from routine daytime attendance in two important ways. First, it often occurred in proximity to major assessments, positioning it as both an academic and social learning event. Second, it typically involved structured advertising and coordinated outreach, increasing student awareness of Math Center services. From a participation perspective, After Dark events may reduce barriers to entry by providing a clearly defined purpose ("exam review night"), a visible time window, and peer presence. For students who might otherwise treat tutoring as a last resort resource, such events could serve as a low friction introduction to the Math Center environment.

Continued Math Center attendance can be interpreted as sustained participation in a structured learning support practice. After Dark exposure might facilitate this transition by converting episodic, assessment-driven attendance into routinized engagement. If the results demonstrated higher continuation probabilities among treated students, this would suggest that structured, well-advertised events could function as entry points into longer-term participation. Conversely, if effects were modest, this indicated that After Dark primarily addressed short-term assessment preparation without substantially altering longer-term engagement trajectories.

Administratively, these findings inform decisions about event-based programming and outreach strategy. If After Dark participation was associated with increased same semester return or accelerated re-engagement, then targeted advertising during early-semester weeks or within key pipeline stages may be an effective strategy for expanding sustained usage. Integrating After Dark programming with early-semester outreach could further align with earlier findings that early engagement predicts continuation.

Taken together, this final analysis connected programmatic intervention, participation theory, and operational outcomes. The fifth research question demonstrates how structured events, aligned with known attendance patterns and curricular rhythms, can influence not only immediate traffic but also longer-term engagement within the Math Center.

Chapter 6

Discussion / Conclusion

The preceding chapters have presented a comprehensive quantitative investigation of student attendance patterns within the Math Center at the University of Oklahoma. Drawing upon detailed electronic check-in data, the study examined how student traffic distributes across courses, time, space, and semesters, and how those patterns inform staffing, service design, and institutional decision making. The central aim was not merely descriptive. Rather, the purpose was to use granular behavioral data to illuminate how students interacted with mathematics support infrastructure and how those patterns can guide operational optimization.

As established in the introductory and theoretical framework sections, existing research demonstrates that MLCs are associated with improved academic outcomes, persistence, and student confidence. However, much of that literature relies on aggregated measures such as total visits or cumulative hours. While valuable, those measures often obscure the internal behavioral structures that shape demand: when students attend, how frequently they return, which courses drive traffic, and how spatial allocation interacts with academic need. This dissertation sought to address that gap by analyzing visitation data through three integrated theoretical lenses: Foot Traffic Analysis, Store Layout and Flow Theory, and Service Operations Management. The findings contribute to mathematics education research by translating operational patterns into interpretable educational phenomena.

We synthesized the findings across all five research questions, situated them within the broader literature, interpreted their institutional implications, and articulated directions for future research. The conclusion now reflects on the broader meaning of viewing an MLC through a service-operations framework grounded in mathematics education concerns.

Research Question 1: Overall Attendance and Course Distribution

The first research question established a foundational understanding of who uses the OU's Math Center and how attendance distributed across mathematics courses. The results revealed clear connections in both unique visitation (breadth of engagement) and total visitation (intensity of engagement). High-enrollment gateway courses consistently generated the largest numbers of unique students and total visits. When normalized by enrollment, courses exceeded 50% utilization, meaning that more than half of enrolled students accessed the Math Center at least once during a semester.

This finding is significant for several reasons. First, it reinforces the well documented role of gateway mathematics courses as structural bottlenecks in undergraduate education. High enrollment combined with elevated anxiety and assessment pressure translates into concentrated support demand. Second, the distinction between unique visitors and total visits revealed an important nuance. Some courses generated broad but shallow engagement (many students visit once), while others generated concentrated repeat traffic (fewer students visit, but they return frequently). This distinction aligns with service-based interpretations of customer acquisition versus retention. Attracting students to visit once is not equivalent to integrating tutoring into their ongoing learning routine.

Room-level analysis further demonstrated that spatial organization mirrors curricular structure. Rooms associated with gateway courses experienced consistently higher traffic, confirming that course assignment to space has direct operational implications. These patterns validate the relevance of viewing an MLC through a zone-based analytic framework comparable to retail department analysis but grounded in curricular architecture.

Research Question 2: Temporal Patterns and Academic Cycles

The second research question examined temporal attendance patterns across days, weeks, semesters, and academic cycles. The data showed consistent clustering of visits around assessment periods and predictable diurnal cycles. Evening sessions often exhibited surges, particularly before coordinated exams. Fall semesters demonstrated higher utilization rates than Spring semesters, likely reflecting incoming student adjustment, enrollment composition, and sequencing of high demand courses.

These findings extend prior research on help-seeking behaviors by providing observable behavioral evidence of reactive versus proactive engagement. Students often concentrated attendance around evaluative pressure points rather than distributing visits evenly throughout the semester. This pattern aligns with recent literature suggesting that mathematics anxiety and assessment contexts shape when students seek academic support. Contemporary research distinguishes between learning-related anxiety and evaluation anxiety, with the latter specifically tied to examinations and performance situations that trigger heightened stress and reactive behaviors. (Moliner, 2020)

Recent work on student behavior in tutoring and learning environments has similarly shown that help-seeking is not uniformly distributed, but instead varies based on contextual and affective factors, including perceived difficulty, performance pressure, and self-regulation. (Moore-Russo, 2025; Egorova, 2024) Emerging research highlights how students' engagement patterns are influenced by their affective states and performance expectations, often leading to delayed or strategically timed help-seeking rather than continuous engagement.

The MLC data thus function as a behavioral trace of broader academic stress cycles, reflecting how affective factors and assessment structures jointly influence help-seeking timing.

Importantly, separating “After Dark” (evening) events from regular operations clarified the distinction between baseline demand and event-driven surges. Just as retail analytics separate promotional sales from routine traffic, isolating these events provided more accurate operational insight. The dramatic increases during these events demonstrate the power of targeted programming and advertising in shaping attendance. They also highlight the necessity of surge planning in staffing models.

Research Question 3: Distinct Student Attendance Patterns

The third research question moved from course-level patterns to individual-level engagement. By analyzing repeat visitation, first and last visit dates, and frequency distributions, the study identified distinct attendance profiles. Some students exhibited single visit behavior; others returned periodically. A subset demonstrated sustained, regular engagement.

This classification mirrors the proactive versus reactive tutoring patterns described in the literature on academic help-seeking (Karabenick & Gonida, 2018). Students who integrate tutoring into their regular study routine represent a fundamentally different behavioral category from those who attend only before exams. From an operational standpoint, these repeat visitors constitute predictable baseline traffic, while exam-driven attendees generate volatility.

The analysis also revealed that course affiliation strongly predicts engagement intensity. Students in gateway courses were more likely to return multiple times, suggesting that structural course characteristics shape ongoing help-seeking. These patterns reinforce the idea that attendance behavior is not random but reflects curricular design, assessment structure, and cumulative content demands.

Research Question 4: Early Attendance and Subsequent Engagement

The fourth research question examined whether early-semester engagement correlates with continued visitation. Students who attended early in the semester were significantly more likely to return in subsequent weeks. This finding has important implications. It suggests that the first visit functions as a threshold event. Once students cross the psychological and logistical barrier of initial attendance, they are more likely to incorporate tutoring into their academic routine.

From a behavioral perspective, early engagement may reduce stigma, increase familiarity with tutors, and build relational trust. From an operational standpoint, early-semester outreach and structured encouragement may serve as high leverage interventions. Encouraging early visits could shift attendance distributions from reactive spikes toward more stable, distributed engagement patterns.

Research Question 5: Optimization of Staffing and Services

The fifth research question translated descriptive findings into operational recommendations. By computing hourly occupancy percentiles and analyzing concurrency patterns, the study generated evidence-based staffing scenarios: balanced (P90), conservative (P95), and surge (maximum observed occupancy). This approach allows administrators to balance cost efficiency against overload risk.

The data revealed that certain hours and rooms consistently approach capacity thresholds, particularly during pre-exam windows. Without percentile-based planning, staffing decisions risk being either insufficient, which would lead to congestion and reduced service quality, or inefficient (i.e., overstaffing low-demand periods). By quantifying occupancy distributions rather than relying on anecdotal impressions, an MLC can adopt a data-driven staffing model aligned with observed demand variability.

The retail and service operations analogies introduced in the theoretical framework were not intended to commercialize education, but to provide analytical tools for interpreting flow, congestion, and resource allocation.

Foot Traffic Analysis proved particularly useful in identifying cyclical demand patterns and peak hours. The Math Center at the University of Oklahoma exhibited predictable weekly and semester-based traffic rhythms analogous to retail cycles; yet these rhythms are anchored in academic calendars rather than consumer trends.

Store Layout and Flow Theory illuminated how room assignment and spatial grouping influence demand density. Because rooms are associated with specific course clusters, curricular changes translate directly into spatial redistribution of traffic.

Service Operations Management Theory provided the strongest contribution to administrative insight. Staffing must respond to overlapping visits rather than simple entry counts. Demand variability is structurally linked to coordinated exams and cumulative content. Thus, the operational lens does not replace mathematics education theory. It complements it by rendering institutional behavior measurable. This study makes several contributions to mathematics education research.

First, it demonstrates that visitation logs are not merely administrative artifacts, but they also include key behavioral data reflecting how students navigate mathematical learning structures. Attendance patterns encode information about curricular pressure points, assessment timing, and affective responses to mathematics.

Second, it advances the argument that granular attendance data offer insights beyond total visit counts. Frequency, timing, and concurrency matter. Two students with identical total hours may represent fundamentally different engagement strategies.

Third, the study provides a replicable methodological template. Other institutions can apply similar data cleaning procedures, temporal decomposition, and occupancy modeling to their own centers. The analytic framework is transferable.

Fourth, the findings support early-intervention strategies. Encouraging first visits early in the semester may increase sustained engagement and reduce reactive attendance spikes.

For administrators, several actionable insights emerge:

1. Gateway courses require disproportionate staffing and spatial allocation.
2. Fall semesters may necessitate elevated baseline staffing relative to Spring, which coincides with course enrollment patterns.
3. Pre-exam windows require surge planning based on historical occupancy percentiles.
4. Early-semester outreach campaigns may increase long-term engagement.
5. After Dark events are effective demand generators and should be strategically integrated into operational planning.

Importantly, data-driven staffing models enhance accountability. Decisions can be justified quantitatively rather than impressionistically, strengthening the case for institutional support and funding.

Limitations

While comprehensive, this study remains observational. It does not establish causal relationships between attendance and academic outcomes. Spatial flow was approximated by room-level data rather than path tracking sensors. Enrollment data integration was partial. Inferred subject codes introduce minor uncertainty.

Nonetheless, these limitations are typical of operational datasets and do not undermine the validity of the patterns identified.

Future Research Directions

Future research could extend this work in several directions. One important avenue would involve linking attendance patterns to course grades and persistence outcomes to better understand how different forms of engagement relate to student success. Building on the operational focus of this study, future work could also integrate tutor scheduling data to examine supply-demand elasticity and evaluate how staffing levels respond to fluctuations in student usage.

Future research should also extend the generalizability and scope of the current analysis. While this study focused on a single institutional context, replicating the framework across multiple universities would allow for comparative analysis and validation of whether observed attendance patterns reflect local institutional structures or broader characteristics of MLCs. Such cross-institutional work would further support the generalization of the MLC as a storefront analytical framework, testing whether concepts drawn from foot traffic analysis, spatial flow, and service operations management consistently apply across diverse academic environments.

In addition, further methodological refinement is warranted in the modeling framework. The negative binomial regression models employed in this study relied on specific baseline course selections and enrollment-normalized offsets. Future work could examine alternative baseline course specifications and model parameterizations to evaluate the robustness and sensitivity of course-level demand estimates. Expanding the temporal scope of the dataset across additional semesters or academic years would also allow for more stable longitudinal inference and improved forecasting of attendance patterns.

A critical extension of this work involves linking attendance behavior to academic performance and long-term student outcomes. While this study identified distinct user profiles (one-time users, consistent users, and super users), future research should examine how these profiles correspond to course grades, persistence in mathematics sequences, and eventual degree completion. Such analysis would provide stronger evidence regarding the educational impact of different patterns of Math Center usage.

Finally, qualitative investigation is necessary to better understand the mechanisms underlying observed behavioral patterns. In particular, the large proportion of one-time users raises important questions: do these students achieve their desired outcomes in a single visit, or do they disengage from the Math Center or the institution altogether? Interviews or survey-based follow-up studies could provide insight into whether limited engagement reflects satisfaction, unmet need, or broader academic disengagement. Linking attendance records to institutional retention data would further clarify whether patterns of limited or discontinued usage correspond to attrition, course withdrawal, or successful progression.

This dissertation began with a central question: how can detailed attendance data illuminate the functioning and optimization of a Mathematics Learning Center? Through systematic data cleaning, temporal decomposition, spatial mapping, and occupancy modeling, the study demonstrated that student visitation patterns are structured, predictable, and deeply connected to the curricular architecture of undergraduate mathematics.

An MLC is not merely a passive support space. It is an active operational system responding to the rhythms of mathematics coursework. Gateway courses generate high-volume demand. Assessment cycles create predictable surges. Early engagement predicts continued participation. Repeat visitation drives service intensity. Staffing must respond to overlapping occupancy rather than simple entry counts.

Viewing an MLC through a service operations lens does not diminish its educational mission. Rather, it strengthens it. By quantifying how students engage with support infrastructure, institutions can align resources more effectively with student needs. The integration of mathematics education theory with organizational and operational analysis provides a richer understanding of how learning support functions in practice.

Ultimately, the findings affirm that Mathematics Learning Centers are both educational and organizational systems. Their effectiveness depends not only on tutor quality and relational dynamics, but also on evidence-based planning, spatial awareness, and data-informed staffing. By leveraging granular behavioral data, institutions can move beyond anecdote toward rigorous, replicable optimization strategies that enhance both efficiency and student success.

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Appendix

Glossary of Terms

The following glossary defines key concepts, measures, methodological terms, course names, and operational phrases used throughout the dissertation. Terms are listed alphabetically to support consistent interpretation of the study's theoretical framework, data structure, analytic procedures, and findings.

After Dark. Special evening review or tutoring sessions hosted by the Math Center prior to major examinations; these sessions were analytically distinguished from routine operations because they generate unusually high attendance surges.

Baseline Operational Flow. The ordinary pattern of Math Center usage during regular operations, examined separately from extraordinary spikes such as After Dark events.

Blue Room. A color-coded Math Center area associated primarily with MATH 1823, MATH 1914, and MATH 2423.

Business Calculus. The common name used for MATH 1743, Calculus I for Business, Life and Social Sciences.

Business Pre-Calculus. The common name used for MATH 1643, Functions and Modeling.

Classification Model. A statistical model used to predict categorical outcomes, such as whether a student will return to the Math Center.

Cluster Analysis. A statistical method used to identify groups of student-semester observations that share similar visitation patterns, timing, or intensity.

Cluster-Robust Standard Errors. A variance adjustment used in regression analysis to account for non-independence among repeated observations from the same student.

Coefficient of Variation. A standardized measure of dispersion used to compare variability in demand across rooms or other categories.

College Algebra. The official course name for MATH 1503.

College Trigonometry. A common alternate name for MATH 1523, Pre-Calculus and Analytical Geometry.

Coordinated Courses. Mathematics courses organized with shared assessments, schedules, or curricular structures, often producing synchronized patterns of tutoring demand.

Coordinated Exam Schedules. Shared examination calendars used by certain mathematics courses that generate predictable spikes in tutoring demand.

Differential and Integral Calculus Sequence. A three-course sequence consisting of MATH 1914, MATH 2924, and MATH 2934.

Diurnal Usage Patterns. Patterns of visitation that vary across times of day, such as morning, afternoon, and evening.

Dominant Course Pattern. The course most consistently associated with a student's visits in a semester, used to infer some missing subject entries.

Dwell Time. A retail analytics concept referring to the time an individual spends in a space; in this study, it parallels session duration in the Math Center.

ECDF. Short for empirical cumulative distribution function, a statistical representation showing the cumulative proportion of observations at or below each value.

Empirical Cumulative Distribution Function. A cumulative distribution tool used to describe how visit counts or similar measures accumulate across student-semester observations.

Enrollment-Normalized Utilization. A standardized measure of Math Center engagement that adjusts for differences in course size by relating visitors to course enrollment.

Exam-Aligned Demand. Math Center demand that rises in conjunction with the timing of examinations, especially in coordinated courses.

Flow. The movement pattern of individuals through a space; in this study, it refers to how students move through the Math Center's physical arrangement.

Foot Traffic. The number of people entering or moving through a space over time.

Foot Traffic Analysis. A theoretical lens adapted from retail research to examine the number, timing, duration, and distribution of student visits in the Math Center.

Functions and Modeling. The official course name for MATH 1643.

Gateway Courses. High-enrollment, prerequisite-intensive courses that function as entry points or bottlenecks within degree pathways and often generate substantial tutoring demand.

Generalized Linear Model. A flexible statistical modeling framework used in the dissertation to analyze count outcomes and other non-normally distributed variables.

Green Room. A color-coded Math Center area associated primarily with MATH 1643 and MATH 1743.

Grey Room. A Math Center room category used for miscellaneous or unspecified visits.

Heavy User. A student whose visitation frequency falls into the highest usage category, often defined in the study as ten or more visits in a semester.

Hourly Aggregation. The process of summarizing visits or occupancy by hour in order to analyze intraday patterns of demand.

Hourly Occupancy. The number of sessions overlapping within a given hour block, used as a proxy for concurrent student load.

Incidence Rate Ratio. The exponentiated coefficient from a count model, interpreted as a multiplicative change in the expected visit rate relative to a reference category.

Inferential Approach. A method of assigning plausible values, such as missing course entries, based on consistent patterns observed within the data.

Interoperability. The capacity of a dataset or file format to be used across different software environments for analysis, replication, or archiving.

Logistic Regression. A statistical method used to estimate the probability of a binary outcome, such as return versus non-return to the Math Center.

Math Anxiety. An affective barrier characterized by tension, worry, or stress associated with mathematics performance and learning.

Math Center. The name used in the dissertation for the specific Mathematics Learning Center at the University of Oklahoma.

Mathematics Learning Center. A campus-based academic support center that provides tutoring, study support, and related mathematics assistance to students.

Mathematics for Critical Thinking. The official course name for MATH 1473.

Model Coefficient. A numerical estimate in a statistical model representing the relationship between a predictor and the outcome variable.

Negative Binomial Regression. A count-data modeling approach used when the variance exceeds the mean, making it more appropriate than Poisson regression for overdispersed visitation data.

Non-Profit Educational Center. An educational support organization guided by mission rather than profit, a framing used in the dissertation to contextualize the Math Center.

Operational Efficiency. The effective use of available resources, such as tutors, time, and rooms, to meet student demand in the Math Center.

Operational Framework. The conceptual structure through which the dissertation interprets tutoring demand, staffing, space, and student usage.

Operational Norms. Expected patterns of center use against which cleaned data were checked for plausibility.

Orange Room. A color-coded Math Center area associated with MATH 1473, MATH 2113, MATH 2223, and MATH 1005 in Fall 2025.

Overdispersion. A condition in count data in which the variance exceeds the mean, violating the Poisson assumption of equidispersion.

Pearson Chi-Square Dispersion Ratio. A diagnostic statistic computed by dividing the Pearson chi-square value by its degrees of freedom to assess whether count data are overdispersed.

Pipeline Stage Indicators. Variables representing a student's position within a course sequence, incorporated into predictive models of return behavior.

Poisson Regression. A count-data model initially considered in the dissertation but found to be unsuitable because the visitation data were substantially overdispersed.

Pre-Calculus and Analytical Geometry. The official course name for MATH 1523.

Principal Component Analysis. A dimensionality-reduction technique used to summarize multivariate patterns and support clustering or density analysis.

Purple Room. A color-coded Math Center area associated primarily with MATH 3113, MATH 3333, and MATH 3413.

Queue Management. The organization of service flow, waiting, and tutor allocation so that student demand can be handled efficiently.

ROC Curve. A graph used in classification analysis to display the tradeoff between sensitivity and specificity across prediction thresholds.

Receiver Operating Characteristic Analysis. A method used to evaluate the performance of classification models by examining how well they distinguish between positive and negative cases.

Red Room. A color-coded Math Center area associated primarily with MATH 2433, MATH 2443, MATH 2924, and MATH 2934.

Regression-Based Methodology. An analytical approach that uses statistical models to estimate relationships while controlling for other relevant variables.

Service Intensity. The amount of tutoring demand generated through both the frequency and duration of student visits.

Service Operations Management Theory. A theoretical lens concerned with how service organizations allocate staff, schedule operations, manage capacity, and maintain service quality in response to demand.

Staffing Optimization. The adjustment of tutor numbers, schedules, and room allocations so that staffing more closely matches observed demand patterns.

Store Layout. The physical arrangement of rooms, sections, entry points, and service areas within a space.

Store Layout and Flow Theory. A theoretical lens adapted from retail analysis to examine how the configuration of space shapes movement, exposure, congestion, and usage.

Storefront. A conceptual description of the Math Center as a visible service environment in which students access tutoring and related support.

Temporal Cycles. Recurring patterns of visitation across time, such as weekday, hourly, or weekly rhythms.

Temporal Patterns. Attendance patterns analyzed by time of day, day of week, week of semester, or semester.

Yellow Room. A color-coded Math Center area associated primarily with MATH 1503 and MATH 1523.