Exploring the Nexus of Teaching and Research Productivity in a Research -Intensive University among STEM Faculty

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Exploring the Nexus of Teaching and Research Productivity in a Research-Intensive University among STEM Faculty

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ABSTRACT

This study examines the relationship between research and teaching productivity among 553 STEM faculty at a public research-intensive university across four disciplines: Biological Sciences, Engineering, Information and Computer Sciences, and Physical Sciences. Using cluster analysis and logistic regression, it investigates how productivity metrics correlate with faculty demographics such as position type, rank, gender, and discipline. The analysis identifies distinct productivity clusters with varied research and teaching outcomes, highlighting significant disparities. These findings underscore the need for institutional policies that support both teaching and research, promoting faculty success. The study provides insights into faculty productivity profiles, informing strategies for efficient and equitable resource distribution, faculty development, and evaluation, ultimately enhancing STEM education and achieving institutional goals.

Keywords: teaching productivity, research productivity, cluster analysis, logistic regression, research-intensive university, STEM Education

INTRODUCTION

Faculty in higher education engage in diverse roles such as research, teaching, and administrative duties (Link et al., 2008). While they contribute to various activities, research productivity—typically measured by publications and grants—remains the primary criterion for success at research-intensive (R1) universities (Schimanski & Alperin, 2018; Cadez et al., 2017). These R1 institutions, classified by the Carnegie system, focus more on research prowess than on teaching or service (Robert & Carlson, 2017). Nonetheless, teaching is still crucial to their mission. Concerns have been raised historically about the potential neglect of undergraduate education due to a heavy focus on research (Kerr, 2001; Lapworth, 2004; Elen et al., 2007). To address these issues, especially amid increasing enrollments and tighter budgets, research universities have turned to lecturers, who are often non-tenured and primarily tasked with teaching (Bampton, 2017; Stenerson et al., 2010; Kezar & Maxey, 2014). This strategic reliance has created distinct groups of faculty dedicated to research or teaching, highlighting the need for a more efficient approach to ensure both missions are adequately supported and remain connected.

Universities have increasingly employed teaching-focused faculty, who spend most of their time on classroom instruction, but unlike lecturers, they also have scholarly and/or service responsibilities (Rawn & Fox, 2018; Harlow et al., 2020; 2022). Despite their growing presence, the contributions of these faculty, compared to traditional research-focused, tenure-track faculty and lecturers, remain underexplored, particularly within research-intensive universities. Previous studies have largely focused on the roles of research-focused faculty and lecturers, such as the impact of contingent faculty on student outcomes (Figlio et al., 2015; Xu & Solanki, 2020). However, the rise of teaching-focused roles that include research duties, alongside the expansion of discipline-based education research, complicates the definition of faculty success (Rawn & Fox, 2018; Harlow et al., 2020). This evolving landscape calls for a reassessment of success metrics as the distinction between teaching and research productivity becomes increasingly blurred. Moreover, while attempts to measure productivity in both domains exist, no universally accepted standards have been established (Prince et al., 2007).

The balance between teaching and research is particularly complex in STEM programs, where faculty benefit from substantial external funding linked to multi-billion-dollar industries (Gibbs et al., 2014). However, STEM fields are also marked by persistent inequities, with minoritized individuals often facing lower success rates in higher education and careers (Casad et al., 2021; Blackwell et al., 2009; White-Lewis et al., 2022). As STEM faculty navigate these challenges, the interplay between teaching and research significantly influences institutional discussions on limited resources, including funding, personnel, and space (Brennan et al., 2019; Healey, 2005). Cultivating a constructive relationship between research and teaching is essential for optimizing university funding and operational efficiency (Healey & Jenkins, 2005). Addressing gaps in this area could offer valuable insights for university administrators and researchers to enhance faculty development and student success (Deem & Lucas, 2006).

This paper examines the relationship between research and teaching productivity metrics and their correlation with STEM faculty demographics, including position type, rank, gender, and discipline. The study focuses on faculty at a University of California (UC) campus, where three primary categories of full-time faculty exist: research-focused faculty, lecturers, and a growing group of tenure-track, teaching-focused faculty (Harlow et al., 2020; 2022; Rozhenkova et al., 2024). By analyzing these metrics, the study aims to enhance understanding of productivity and provide recommendations for resource allocation, faculty development, and recruitment and retention strategies. Specifically, our research questions (RQs) are:

1. How are research and teaching productivity interrelated?
2. To what extent do faculty vary in terms of their research and teaching productivity metrics?
3. How do faculty characteristics (*faculty type, tenure-status, discipline, and gender*) relate to the observed teaching and research productivity?

LITERATURE REVIEW

Research and Teaching Productivity

Faculty productivity is generally divided into research and teaching metrics, and there is no universally accepted way to measure each (Marsh & Hattie, 2002). For research productivity, common indicators include the volume of peer-reviewed journal publications, the journal's impact factor, and the number of times these publications are cited. These criteria capture a researcher's influence and the dissemination of their work within the scholarly community (Bak & Kim, 2015). Additionally, acquiring external grant funding is a key measure, highlighting a researcher's competitiveness in securing financial support and the perceived merit and viability of their work (Fairweather, 2002). Furthermore, participation in conferences and workshops is recognized as part of a faculty's research output (Fairweather, 2002; Webber et al., 2013). Together, these metrics seek to offer a holistic view of a researcher's contributions, although there are ongoing debates over the emphasis on quantity versus quality of academic work (Marsh & Hattie, 2002; Griffiths, 2004).

For teaching productivity, one common metric is the number of classroom-contact-hours as a tangible metric of teaching commitment (Fairweather, 2002, 2005; Santo et al., 2009; Webber et al., 2013). Additionally, student evaluations of teaching have been widely used (Balam & Shannon, 2010; Bedggood & Donovan, 2012; Uttl et al., 2017; Zabaleta, 2007; Penny, 2003; Webber et al., 2013), as they provide direct feedback on instructor effectiveness, clarity, and engagement from the learner's perspective despite debates over their reliability and bias (Marsh & Hattie, 2002). Other methods include assessing achievement of student learning outcomes, such as grades or performance on standardized assessments, to gauge the impact of instruction on student achievement (Palali et al., 2018). However, there is still considerable debate as to whether these measurement metrics effectively capture the essence of teaching productivity (Benton & Cashin, 2014).

Research and Teaching Productivity Nexus

Perspectives on the relationship between faculty research and teaching productivity vary. Some scholars argue that research and teaching reinforce each other, with activities in one domain supporting the other (Cadez et al., 2017; Galbraith & Merrill, 2012; Schapper & Mayson, 2010; Becker & Kennedy, 2005). Others caution that a strong focus on research may detract from teaching, overshadowing undergraduate education (Jonker & Hicks, 2014). Fairweather (2002) notes that prioritizing one often reduces attention to the other, while Winslow (2010) found research can marginally improve teaching, especially in research-intensive settings. Xu and Solanki (2020) and Keller et al. (2017) argue that integrating research into teaching enhances pedagogy, leading to better student outcomes. Conversely, some propose that teaching and research are distinct, with success in one not necessarily affecting the other (Figlio & Schapiro, 2017; Marsh & Hattie, 2002). Hattie and Marsh (2002) identified almost no correlation between the two, suggesting they operate independently. Morales et al. (2017) found that supervising undergraduate research relates to a faculty's h-index and funding, indicating contributions to training future academics benefit research productivity. These mixed findings highlight the complex dynamics between teaching and research, emphasizing the need to consider the variables, methodologies, faculty roles, and demographics when evaluating productivity.

Research and Teaching Productivity in the Context of Faculty Demographics

Type and Rank. Faculty types, such as lecturers, research faculty (RF), and teaching faculty (TF), have distinct roles that shape their productivity and contributions. Lecturers primarily focus on teaching and are evaluated accordingly (Beth & Lee, 2020). RF are mainly assessed on their research, reflecting a research-over-teaching bias in research-intensive institutions (Brew, 2010). TF are expected to balance high-quality teaching with research and service (Bush et al., 2011; Harlow et al., 2022; Healey et al., 2016; Prince et al., 2007). Despite these role distinctions, overlaps exist, with lecturers, tenure-track TF, and RF often engaging in both teaching and research, necessitating an empirical approach to accurately capture their contributions.

Faculty rank (assistant, associate, full) also significantly influences responsibilities (Beth & Lee, 2020; Scott & Danley-Scott, 2015). Assistant professors face pressure to establish research while adapting to teaching (Hesli & Lee, 2013; Monroe et al., 2008). Tenured associate and full professors enjoy job stability, enabling long-term research but with greater service obligations (Singh & Stoloff, 2003). Lecturers, though sometimes granted longer-term contracts, continue to prioritize teaching (Shayne, 2019). These factors underscore the complex nature of academic roles, where different ranks present unique challenges and opportunities in balancing research and teaching.

Gender. Gender disparities in faculty productivity have long been debated. Historically, female faculty have shown lower research productivity and higher teaching loads than males, often due to unequal resource access, fewer funding opportunities, and greater service demands (Astin & Davis, 2019; Santo et al., 2009; Xu, 2008; Maphalala & Mpofu, 2017; Misra et al., 2012; Boring & Ottoboni, 2016). However, recent studies indicate these disparities lessen when accounting for discipline, tenure status, and family commitments (Ceci & Williams, 2011; Fox, 2005). Ginther et al. (2011) found no significant gender differences in grant success with bias-minimized reviews, and Marschke et al. (2007) reported equal teaching loads across genders when considering rank and department. Despite these findings, ongoing debates highlight the need for further empirical research on gender disparities in faculty productivity.

Discipline. Productivity metrics vary widely across disciplines due to differences in publication norms, funding, and teaching demands (Sinha et al., 2013). STEM faculty often publish more and secure more funding than humanities faculty, who may focus on longer-term projects like books that typical metrics overlook (Lee & Bozeman, 2005). Teaching loads also differ: science and engineering faculty generally teach less but have more research duties, while humanities and social sciences faculty face heavier teaching loads (Shin & Cummings, 2010). Even within STEM, publication and patent rates vary by field and often don't align (Dietz & Bozeman, 2005; Pinheiro et al., 2014; Lee, 2024). Interdisciplinary researchers may struggle with traditional metrics, as their work spans multiple fields and doesn’t fit conventional journals (Leahey et al., 2017). These variations highlight the limitations of current evaluation frameworks in capturing the unique characteristics of each discipline (Fairweather, 2002).

METHODS

Data

This study analyzed data from 553 full-time STEM faculty at a public, research-intensive UC institution in the western United States from 2011 to 2017. The faculty belonged to four STEM units: School of Biological Sciences, School of Engineering, School of Information and Computer Sciences, and School of Physical Sciences. Research productivity data were sourced from SciVal, Elsevier's benchmarking tool (Elsevier, 2024), focusing on research publications and external grant funding. Teaching productivity data came from faculty-level course records during the study period. Exclusion criteria included part-time faculty, faculty with no research productivity, and those who did not teach during the study period.

Faculty Demographics

Faculty demographic data includes faculty type (lecturer, RF, TF), rank (non-continuing, continuing, assistant, associate, full), discipline (Biological Sciences, Engineering, Information and Computer Sciences, Physical Sciences), and gender. Lecturers are either non-continuing or continuing, with continuing lecturers having at least six years of service and qualifying for longer-term contracts. RF and TF are ranked as assistant, associate, or full professors. A 'Faculty Tenure-Status' field was created to distinguish lecturer ranks (non-continuing, continuing) from RF and TF ranks (assistant, associate, full). Continuing lecturers, with renewable contracts, are treated as tenured, while non-continuing are not. Assistant RF and TF are non-tenured, whereas associate and full professors are tenured.

The majority of faculty were RF (n=486; 88%), with lecturers (n=33; 6%) and TF (n=34; 6%) being smaller groups (Table 1). Most research and teaching professors were full professors (n=296; 54%), followed by assistant (n=133; 24%) and associate professors (n=91; 16%). Non-continuing and continuing lecturers comprised 4% (n=22) and 2% (n=11) of the sample, respectively. In discipline terms, the School of Biological Sciences had no lecturers but included 23% of RF (n=113) and 41% of TF (n=14). The School of Engineering had 26% of RF (n=124) and 9% of TF (n=3). The School of Information and Computer Sciences had 36% of lecturers (n=12), 17% of RF (n=81), and 15% of TF (n=5). The School of Physical Sciences had the most lecturers (n=18; 55%), the highest RF proportion (n=168; 35%), and the second-highest TF proportion (n=12; 35%).

Table 1. Faculty Demographics by Faculty Type, Rank, and Discipline

Faculty Type/Rank	Faculty Tenure-Status	School of Physical Sciences	School of Engineering	School of Biological Sciences	School of Information and Computer Sciences
Lecturers					
Non-Continuing	Non-tenured	13	2	0	7
Continuing	Tenured	5	1	0	5
Total		18	3	0	12
Teaching Faculty (TF)					
Assistant	Not-yet-tenured	8	2	8	1
Associate	Tenured	3	1	3	3
Full	Tenured	1		3	1
Total		12	3	14	5
Research Faculty (RF)					
Assistant	Not-yet-tenured	35	31	32	16
Associate	Tenured	25	23	16	17
Full	Tenured	108	70	65	48
Total		168	124	113	81
Grand Total		198	130	127	98

Table 2 presents the demographic data highlighting that the majority of faculty across all disciplines were male (Females=133, 24%; Males=420, 76%)

Table 2. Faculty Demographics by Gender and Discipline

Gender	School of Physical Sciences	School of Engineering	School of Biological Sciences	School of Information and Computer Sciences
Male	151	107	90	72

Female	47	23	37	26
Total	198	130	127	98

During the study, we evaluated eight teaching productivity metrics: the total number of lower-division (LD), upper-division (UD), undergraduate independent research (IR), and graduate (GR) courses taught, along with average student enrollment per course section. Additionally, we assessed eight research productivity metrics: average citation count, citations per work, field-adjusted citation influence, h-index, production in the top decile of citations, publications in top-decile journals by cite score, total scholarly contributions, and total research grants received. Definitions, data sources, and summary statistics for each metric are detailed in the supplemental materials (Appendices A, B).

Data Transformation and Standardization

Given the significant skewness in the distribution of each of the teaching and research productivity attributes, it was necessary to transform the data prior to analysis. We first applied a logarithmic transformation ($\log(x + 0.5)$) and then we standardized the log-transformed values using the formula:

$$z = \frac{\log(x + 0.5) - mean(\log(x + 0.5))}{standard\ deviation\ (\log(x + 0.5))}$$

so that each of the standardized teaching and research productivity attributes would have a mean of zero and a standard deviation of one. This process ensures that attributes with broader ranges do not disproportionately affect the calculation of the correlation matrix and the distance metrics during the cluster data analysis (Kandel et al, 2012).

Data Analysis

RQ1: How are research and teaching productivity interrelated?

To answer RQ1, we examined the correlation matrix between the standardized research and teaching productivity metrics. First, we examined the correlation within the standardized research metrics. Second, we examined the correlation within the standardized teaching metrics. Lastly, we examined the correlations between the standardized research and teaching productivity metrics.

RQ2: To what extent do faculty vary in terms of their research and teaching productivity metrics?

We grouped faculty into clusters based on similarities in research and teaching productivity metrics to address RQ2. Cluster analysis helped us form homogeneous groups within clusters while ensuring they remain distinct from each other (Kandel et al., 2012). We used the NbClust package in R (Charrad et al., 2014) to determine the optimal number of clusters by analyzing standardized productivity metrics. Hierarchical clustering with complete linkage and 30 different indices was employed to identify the optimal cluster count. While the number of clusters is not predetermined, following the cluster analysis, we compared the standardized with the transformation values of the research and teaching productivity metrics across the resultant clusters using analysis of variance (ANOVA) and the Kruskal-Wallis tests (Jamil & Khanam, 2024; Ostertagova et al., 2014) to confirm differences and validate the heterogeneity among the clusters.

RQ3: How do faculty characteristics (faculty type, tenure-status, discipline, and gender) relate to the observed teaching and research productivity?

After cluster analysis, we compared faculty characteristics against the likelihood of belonging to specific clusters using logistic regression (Hosmer & Lemeshow, 2013; Bhattacharjee & Karade, 2018). A separate logistic regression model was applied for each cluster. Predictor variables included faculty type (lecturers, TF, RF), tenure-status (non-tenured, tenured), discipline (Biological Sciences, Engineering, Information and Computer Sciences, Physical Sciences), and gender (female and male). The response variable is whether the faculty is in the resultant cluster. The model is given by:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

For each categorical predictor, a reference group (RG) was selected based on prevalence. RF is the RG for faculty type, tenured for tenure-status, the School of Biological Sciences for discipline, and female for gender.

RESULTS

RQ1: How do research and teaching productivity metrics interrelate?

The correlation matrix (Table 3) reveals the relationships among the eight research productivity metrics, showing strong positive correlations for most. "Average citation count" is notably correlated with "Average citation per publication" (r=0.948) and "Average h-index" (r=0.899), indicating that higher citation counts are associated with higher citations per publication and h-index values. "Average field-weighted citation impact" also shows strong correlations with "Average citation count" (r=0.890) and "Average citation per publication" (r=0.912). Additionally, "Average scholarly outcome" correlates significantly with "Average h-index" (r=0.855). In contrast, "Sum of grant awards" shows more moderate correlations, with the highest being with "Average scholarly outcome" (r=0.477), indicating that faculty with higher amounts of grant dollars also tend to have higher scholarly output. Overall, the matrix reveals a strong interconnectivity among citation-related metrics.

Table 3. Research Productivity Correlation Matrix

Research Productivity Metrics	RP1	RP2	RP3	RP4	RP5	RP6	RP7	RP8
(RP1) Average citation count	-							
(RP2) Average citation per publication	0.948	-						
(RP3) Average field-weighted citation impact	0.890	0.912	-					
(RP4) Average h-index	0.899	0.825	0.749	-				
(RP5) Average top 10% citation percentile	0.849	0.868	0.788	0.712	-			
(RP6) Average publication top 10 citescore	0.830	0.839	0.717	0.797	0.756	-		
(RP7) Average scholarly outcome	0.888	0.710	0.702	0.855	0.682	0.683	-	

(RP8) Sum of grant awards ($)	0.457	0.399	0.360	0.442	0.421	0.413	0.477	-

The correlation matrix in Table 4 shows relationships among eight teaching productivity metrics. Key findings include a strong correlation between "average enrollments per lower division (LD) course" and "total LD courses taught" (r=0.856), indicating that faculty who teach more LD courses also have higher enrollments. Similarly, "average enrollments per upper division (UD) course" correlates with "total UD courses taught" (r=0.798), suggesting that those teaching more UD sections also handle larger enrollments. "Average undergraduate independent research (IR) enrollments per term" strongly correlates with "total terms mentoring undergraduate IR courses" (r=0.883), meaning faculty mentoring more IR students do so over multiple terms. For graduate (GR) courses, "average enrollments per GR course" correlates with "total GR courses taught" (r=0.850), indicating that faculty teaching more GR sections also have higher enrollments. Overall, the matrix shows that enrollment metrics are closely linked to the number of courses taught within a specific course type (LD, UD, IR, GR) but not across different course types. This suggests variability in teaching productivity among faculty, underscoring that teaching assignments cannot follow a one-size-fits-all approach.

Table 4. Teaching Productivity Correlation Matrix

Teaching Productivity Metrics	**TP1**	**TP2**	**TP3**	**TP4**	**TP5**	**TP6**	**TP7**	**TP8**
(TP1) Average enrollment LD	-							
(TP2) Average enrollment UD	-0.206	-						
(TP3) Average enrollment IR	-0.153	0.193	-					
(TP4) Average enrollment GR	-0.154	0.149	-0.078	-				
(TP5) Total LD courses	0.856	-0.210	-0.175	-0.239	-			
(TP6) Total UD courses	-0.142	0.798	0.204	0.125	-0.102	-		
(TP7) Total IR terms	-0.123	0.185	0.883	-0.081	-0.153	0.208	-	

(TP8) Total GR courses	-0.121	0.150	-0.082	0.850	-0.198	0.137	-0.072	-

The final correlation matrix (Table 5) shows the relationships between eight teaching and eight research productivity metrics. The analysis reveals generally low to moderate correlations between these metrics. Notably, "average number of undergraduate IR enrollments per term" has weak positive correlations with several research metrics, such as "average citation count" (r=0.192), "citations per publication" (r=0.225), "h-index" (r=0.194), and "top 10% citation percentile" (r=0.221), indicating a weak link between contributions to undergraduate IR and increased research productivity. Similarly, "average enrollments per GR course" is weakly correlated with "h-index" (r=0.216) and "scholarly outcome" (r=0.285), and moderately correlated with "sum of grant awards" (r=0.420), suggesting that higher enrollments in graduate courses are associated with greater grant funding. The strongest correlation, though still moderate, is between "total GR courses taught" and "sum of grant awards" (r=0.455), indicating that faculty who teach more GR courses tend to receive more grant funding. In contrast, "total LD courses taught" shows weak negative correlations with research metrics like "average citation count" (r=-0.131) and "h-index" (r=-0.122), implying that faculty with lower research productivity often teach more LD courses. Overall, the matrix suggests some positive associations between teaching and research productivity, but these relationships are generally weak, with external funding showing the strongest, yet modest, correlation related to mentoring undergraduate IR and teaching GR courses.

Table 5. Teaching and Research Productivity Correlation Matrix

	RP1	**RP2**	**RP3**	**RP4**	**RP5**	**RP6**	**RP7**	**RP8**
TP1	-0.031	0.001	-0.038	-0.034	-0.004	0.006	-0.082	-0.081
TP2	0.032	0.030	0.037	0.052	0.030	0.081	0.040	0.188
TP3	0.192	0.225	0.115	0.194	0.221	0.204	0.120	0.212
TP4	0.208	0.126	0.160	0.216	0.080	0.171	0.285	0.420
TP5	-0.131	-0.100	-0.119	-0.122	-0.109	-0.112	-0.168	-0.203
TP6	0.014	0.017	0.010	0.061	0.003	0.073	0.016	0.155
TP7	0.214	0.271	0.139	0.212	0.244	0.235	0.108	0.236
TP8	0.227	0.140	0.176	0.256	0.102	0.202	0.316	0.455

RQ 2: To what extent do faculty vary in terms of their research and teaching productivity metrics?

The cluster analysis identified three distinct profiles using eight research and eight teaching productivity metrics. Research productivity levels varied distinctly across the clusters, while teaching productivity differed by course level. Cluster 1 (C1) has high research productivity, with teaching productivity being low in lower division (LD) courses, moderate in upper division (UD) and graduate (GR) courses, and high in independent research (IR) mentorship. Cluster 2 (C2) shows moderate research productivity with high teaching productivity in LD and GR courses, moderate in UD courses, and low in IR mentorship. Cluster 3 (C3) displays low research productivity and high teaching productivity in LD courses, but low in UD, GR courses, and IR mentorship. Detailed summary statistics for each cluster's productivity metrics are available in Appendix C of the supplemental materials.

Table 6 highlights significant differences in both research and teaching productivity metrics across the three clusters ($p<0.05$). Each research productivity metric showed substantial variations between the clusters, indicating distinct levels of research performance. Similarly, all teaching productivity metrics also demonstrated significant differences across the clusters, underscoring the distinctiveness of teaching and research productivity within each cluster.

Table 6. ANOVA and Kruskal-Wallis Analysis of Research and Teaching Productivity Across Three Clusters

Research, Teaching Productivity Metrics	**ANOVA**		**Kruskal-Wallas**
	F-value	***p***	***p***
RP1	946.3	< 0.001	< 0.001
RP2	756.1	< 0.001	< 0.001
RP3	694.9	< 0.001	< 0.001
RP4	669.8	< 0.001	< 0.001
RP5	346.9	< 0.001	< 0.001
RP6	334.6	< 0.001	< 0.001
RP7	327.8	< 0.001	< 0.001
RP8	71.3	< 0.001	< 0.001
TP1	54.4	< 0.001	< 0.001
TP2	5.1	0.01	0.03

TP3	39.5	< 0.001	< 0.001
TP4	19.3	< 0.001	< 0.001
TP5	50.1	< 0.001	< 0.001
TP6	6.6	< 0.001	0.01
TP7	48.9	< 0.001	< 0.001
TP8	22.6	< 0.001	< 0.001

Figure 1 uses a heatmap to visualize the median values of each research and teaching productivity metric across the clusters, showing a color-coded representation of each metric's magnitude. Table 7 further details the characteristics of each cluster as derived from the heatmap.

Figure 1. Teaching and Research Productivity Heatmap by Cluster

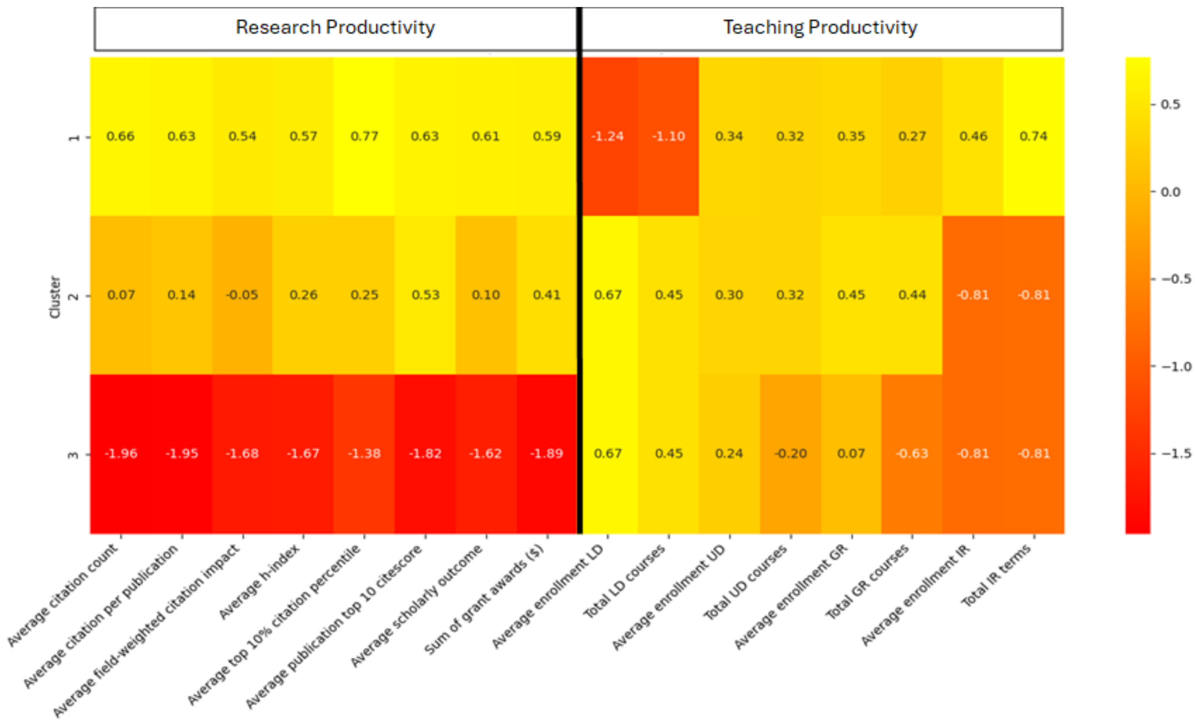

Table 7. Cluster Characteristics Summary

Cluster	**Description**

C1	• C1 generally has the highest median (med) values across all research metrics than C2 and C3.
	   o This cluster excels in “average top 10% citation percentile” (med=0.77), “average publication top 10 citescore” (med=0.63), and “sum of grant awards” (med=0.59), indicating strong top-tier publication presence.
	• Teaching productivity metrics show greater variability than research productivity metrics.
	   o Negative values for lower-division (LD) course metrics (“average enrollments per LD course,” med=-1.24; “total LD courses taught,” med=-1.10) indicate low teaching productivity in LD courses.
	   o Moderate values for upper-division (UD) (“average enrollments per UD course,” med=0.34; “total UD courses taught,” med=0.32) and graduate-level (GR) courses (“average enrollments per GR course,” med=0.35; “total GR courses taught,” med=0.27) suggest moderate teaching productivity.
	   o High values for undergraduate independent research (IR) mentoring courses (“average enrollments per IR course,” med=0.46; “total terms mentoring IR courses,” med=0.74) indicate high teaching productivity in IR courses.

C2	• C2 generally has moderate median (med) values across all research metrics compared to C1 and C3. • Teaching productivity metrics show more variability than research productivity metrics.

	○ Negative values for undergraduate independent research (IR) mentoring metrics ("average enrollments per IR course," med=-0.81; "total terms mentoring IR courses," med=-0.81) indicate low teaching productivity in IR courses. ○ Moderate values for upper-division (UD) metrics ("average enrollments per UD course," med=0.30; "total UD courses taught," med=0.32) suggest moderate teaching productivity in UD courses. ○ High values for lower-division (LD) ("average enrollments per LD course," med=0.67; "total LD courses taught," med=0.45) and graduate-level (GR) metrics ("average enrollments per GR course," med=0.45; "total GR courses taught," med=0.44) indicate high teaching productivity in LD and GR courses.
C3	• C3 generally has low median (med) values, all negative, across all research metrics compared to C1 and C2. • Teaching productivity metrics show more variability than research metrics. ○ Negative values in undergraduate independent research (IR) mentoring metrics ("average enrollments per IR course," med=-0.81; "total terms mentoring IR courses," med=-0.81) indicate low teaching productivity in IR courses. ○ Significantly low values in upper-division (UD) ("average enrollments per UD course," med=0.07; "total UD courses taught," med=-0.20) and graduate-level (GR) metrics ("average enrollments per GR course," med=0.07; "total GR courses taught," med=-0.63) indicate low teaching productivity in UD and GR courses.

RQ3: How do faculty characteristics (faculty type, rank, discipline, and demographic) correlate with the observed teaching and research productivity relationship?

Cluster Overview by overlaying the Faculty Demographics

Faculty characteristics including type (RF, TF, lecturers), rank (non-continuing lecturer, continuing lecturer, assistant, associate, full professor), gender (male, female), discipline (Physical Sciences, Engineering, Biological Sciences, Information and Computer Sciences), and the number of terms taught during the study period were compared across three clusters. The detailed comparisons are presented in Tables 8-10.

Cluster 1 (C1) comprises 217 faculty members, predominantly male (Males=169, 78.9%; Females=48, 22.1%). This high research productivity cluster consists almost entirely of RF (n=216, 99.5%), accounting for 44.4% of all RFs in the study. The School of Biological Sciences leads in discipline representation with 77 members, followed by the School of Engineering (n=52), the School of Physical Sciences (n=51), and the School of Information and Computer Sciences (n=36). The rank distribution includes mostly Full Professors (n=118), Assistant Professors (n=63), and Associate Professors (n=35). Only one TF, an Assistant Professor from the School of Biological Sciences, is in this cluster, with no lecturers present. Faculty in C1 taught an average of 9.6 terms during the study, with teaching commitments spanning 1.9 terms in lower division (LD) courses, 4.8 in upper division (UD) courses, 4.7 in graduate (GR) courses, and 9.2 in undergraduate independent research (IR) courses.

Cluster 2 (C2) is the largest with 234 faculty, mostly male (Males=177, 75.6%; Females=57, 24.4%). It comprises predominantly RF (n=210, 89.7%), accounting for 43.2% of all RFs in the study. The School of Physical Sciences leads in discipline representation (n=96), followed by the School of Engineering (n=58), the School of Information and Computer Sciences (n=29), and the School of Biological Sciences (n=27). Most members are Full RFs (n=144), with Assistant Professors (n=34) and Associate Professors (n=32) following. There are a few Lecturers (n=8), mainly non-continuing (n=6) from the School of Information and Computer Sciences (n=5). The cluster also includes several tenure-track TFs (n=16, 6.8%), nearly half (47.1%) of all TFs in the study, mostly Assistant Professors in the School of Biological Sciences (n=9) and Physical Sciences (n=6). C2 faculty have the highest teaching workload across all clusters, averaging 12.7 terms taught, including 4.8 in lower division (LD) courses, 5.2 in upper division (UD) and graduate (GR) courses, and 3.8 in undergraduate independent research (IR) courses.

Cluster 3 (C3) is the smallest with 102 faculty, predominantly male (Males=74, 72.5%; Females=28, 27.5%). It has fewer RF (n=60, 58.8%), representing 12.3% of all RFs in the study. The School of Physical Sciences has the most faculty (n=21), followed by the School of Information and Computer Sciences (n=16), School of Engineering (n=14), and the School of Biological Sciences (n=9). Most members are Full Professors (n=32), with Assistant Professors (n=24) and Associate Professors (n=21) next. C3 includes the most lecturers (n=25, 24.5%), 75.8% of all lecturers in the study, mainly in the School of Physical Sciences (n=16) and Information and Computer Sciences (n=7). There are also several tenure-track TFs (n=17, 16.7%), half of all TFs in the study. C3 faculty have the second-highest teaching workload, averaging 10.7 terms taught, including 5.7 in lower division (LD) courses, 4.1 in upper division (UD) courses, 2.7 in graduate (GR) courses, and 1.4 in undergraduate independent research (IR) courses.

Table 8. Gender, Faculty Type, and Rank Comparison by Clusters

	Cluster 1	**Cluster 2**	**Cluster 3**	***p***
Gender				0.58
Female	48	57	28	
Male	169	177	74	
Faculty Type/Rank				
Lecturers	0	8	25	0.69[a]
Non-continuing	0	6	16	
Continuing	0	2	9	
Teaching Faculty (TF)	1	16	17	0.48[a]
Assistant	1	11	7	
Associate	0	3	7	
Full	0	2	3	
Research Faculty (RF)	216	210	60	< 0.001
Assistant	63	34	17	
Associate	35	32	14	
Full	118	144	29	
Total	217	234	102	

Note: Chi-square test used unless otherwise noted. a Fisher's exact test used.

Table 9. Discipline Comparison by Clusters

Cluster	**Faculty Type/Rank**	**School of Physical Sciences**	**School of Engineering**	**School of Biological Science**	**School of Information and Computer Sciences**
1	Teaching Faculty (TF)	0	0	1	0
	Assistant	0	0	1	0
	Research Faculty (RF)	51	52	77	36
	Assistant	15	13	27	8
	Associate	7	11	8	9
	Full	29	28	42	19
	Total	51	52	78	36
2	Lecturers	2	1	0	5
	Non-continuing	2	1	0	3
	Continuing	0	0	0	2
	Teaching Faculty (TF)	6	0	9	1

	Assistant	5	0	5	1
	Associate	1	0	2	0
	Full	0	0	2	0
	Research Faculty (RF)	96	58	27	29
	Assistant	15	12	3	4
	Associate	15	9	4	4
	Full	66	37	20	21
	Total	104	59	36	35
3	Lecturers	16	2	0	7
	Non-continuing	11	1	0	4
	Continuing	5	1	0	3
	Teaching Faculty (TF)	6	3	4	4
	Assistant	3	2	2	0
	Associate	2	1	1	3
	Full	1	0	1	1
	Research Faculty (RF)	21	14	9	16
	Assistant	5	6	2	4
	Associate	3	3	4	4
	Full	13	5	3	8
	Total	43	19	13	27
Grand Total		198	130	127	98

Table 10. Comparison of the Average Teaching Terms by Clusters

	Cluster 1	**Cluster 2**	**Cluster 3**	***F***	***p***
Average # of Terms Taught	9.6	12.7	10.7	15.41	< 0.001
Lower Division	1.9	4.8	5.7	27.53	< 0.001
Upper Division	4.8	5.2	4.1	12.11	< 0.001
Graduate Level	4.7	5.2	2.7	13.16	< 0.001
Independent Research Mentoring	9.2	3.8	1.4	39.59	< 0.001

There was no significant difference in gender distribution across the clusters (p=0.58, Table 8), nor in faculty rank among lecturers (p=0.69) and tenure-track TF (p=0.48). The lack of significant differences in lecturer and TF ranks may be due to the small sample sizes, which could limit the statistical power to detect differences. Conversely, there was a significant difference in the distribution of faculty rank among RF across the clusters (p<0.001). Additionally, significant differences were observed in the average number of terms faculty taught at the LD, UD, GR levels, and in mentoring IR courses across the clusters (p<0.001, Table 10).

The logistic regression analysis in Table 11 models the likelihood of faculty being in C1. Faculty on the tenure track but not yet tenured were more likely to be in C1 (OR=2.01, p=0.01). Faculty from the Biological Sciences were more likely to be in C1 compared to other disciplines: School of Engineering (OR=0.26, p<0.001), School of Information and Computer Sciences (OR=0.29, p<0.001), and School of Physical Sciences (OR=0.17, p<0.001). There was no significant difference in the odds of being in C1 between male and female faculty once rank and faculty type were controlled for (OR=1.46, p=0.16).

Table 11. Cluster 1 Logistic Regression Coefficient Summary

	β	**OR**	**SE**	**95% CI [LL, UL]**	**z**	**P>|z|**
Intercept	0.47	1.60	0.32	[-0.16, 1.09]	1.47	0.14
Faculty Tenure-Status						
RG: Tenured						
Not-yet-tenured status	0.70	2.01	0.26	[0.19, 1.22]	2.67	0.01
Discipline						
RG: School of Biological Sciences						
School of Engineering	-1.35	0.26	0.32	[-1.97, -0.73]	-4.27	< 0.001
School of Information and Computer Science	-1.24	0.29	0.34	[-1.91, -0.56]	-3.6	< 0.001
School of Physical Sciences	-1.79	0.17	0.3	[-2.38, -1.19]	-5.89	< 0.001
Gender						
RG: Female						
Male	0.38	1.46	0.27	[-0.15, 0.91]	1.4	0.16

** Logistic regression for Cluster 1 is conducted exclusively considering Research Faculty (RF).*

Table 12 presents a logistic regression analysis on the odds of faculty being in C2. Female, tenured, Biological Sciences RF faculty are less likely to be in C2 (OR=0.50, p=0.02). The effect of faculty type varies: lecturers showed a non-significant decrease in log-odds by 0.84, while TF exhibited a non-significant increase by 0.21, suggesting TF are more likely to be in C2 than lecturers, although these findings were not statistically significant (p>0.05). Non-tenured faculty showed a minimal and non-significant effect (p=0.98), but tenure-track, not-yet-tenured faculty had a significant decrease in log-odds by 0.57 (p=0.02). Faculty from the School of Engineering (OR=2.05, p=0.02) and School of Physical Sciences (OR=3.29, p<0.001) were more likely to be in C2 compared to the School of Biological Sciences. There was no significant difference in the odds of being in C2 between males and females when controlling for faculty type and rank (OR=0.83, p=0.45).

Table 12. Cluster 2 Logistic Regression Coefficient Summary

	β	**OR**	**SE**	**95% CI [LL, UL]**	**z**	**P>|z|**
Intercept	-0.70	0.50	0.3	[-1.29, -0.10]	-2.30	0.02
Faculty Type						
RG: Research Faculty (RF)						
Lecturers	-0.84	0.43	0.87	[-2.54, 0.86]	-0.97	0.33
Teaching Faculty	0.21	1.23	0.44	[-0.65, 1.08]	0.49	0.63
Faculty Tenure-Status						
RG: Tenured						
Non-tenured	0.03	1.03	1.02	[-1.98, 2.03]	0.03	0.98
Not-yet-tenured	-0.57	0.57	0.25	[-1.06, -0.08]	-2.28	0.02
Discipline						
RG: School of Biological Sciences						
School of Engineering	0.72	2.05	0.31	[0.12, 1.32]	2.34	0.02
School of Information and Computer Science	0.44	1.55	0.33	[-0.20, 1.07]	1.34	0.18
School of Physical Sciences	1.19	3.29	0.28	[0.65, 1.74]	4.3	< 0.001
Gender						
RG: Female						
Male	-0.19	0.83	0.25	[-0.67, 0.30]	-0.75	0.45

Table 13 exhibits logistic regression analysis on the odds of faculty being in C3. The baseline reference groups (RF for faculty type, tenured for tenure-status, School of Biological Sciences for discipline, and female for gender) were significantly less likely to be in C3 (OR=0.07, p<0.001). Lecturers (OR=14.44, p<0.001) and TF (OR=9.30, p<0.001) had significantly higher odds of being in C3 compared to RF. For tenure-status, non-tenured faculty showed a non-significant decrease in log-odds (0.24, p=0.82), and not-yet-tenured faculty had a negligible effect (0.01, p=0.98). Faculty from the School of Information and Computer Sciences were more likely to be in C3 compared to those from the School of Biological Sciences (OR=2.72, p=0.03). There was no significant difference in the odds of males being in C3 compared to females when accounting for faculty type, tenure-status, and discipline (OR=1.28, p=0.48).

Table 13. Cluster 3 Logistic Regression Coefficient Summary

	β	OR	SE	95% CI [LL, UL]	z	P>|z|
Intercept	-2.68	0.07	0.47	[-3.60, -1.76]	-5.69	< 0.001
Faculty Type						
RG: Research Faculty (RF)						
Lecturers	2.67	14.44	0.87	[0.96, 4.38]	3.06	< 0.001
Teaching Faculty	2.23	9.30	0.46	[1.32, 3.14]	4.81	< 0.001
Faculty Tenure-Status						
RG: Tenured						
Non-tenured	-0.24	0.79	1.02	[-2.23, 1.76]	-0.23	0.82
Not-yet-tenured	0.01	1.01	0.34	[-0.66, 0.68]	0.03	0.98
Discipline						
RG: School of Biological Sciences						
School of Engineering	0.31	1.36	0.48	[-0.63, 1.24]	0.64	0.52
School of Information and Computer Science	1.00	2.72	0.45	[0.12, 1.87]	2.23	0.03
School of Physical Sciences	0.66	1.93	0.41	[-0.14, 1.46]	1.62	0.11
Gender						
RG: Female						
Male	0.25	1.28	0.35	[-0.44, 0.93]	0.71	0.48

DISCUSSION

This study contributes to the discussion on research and teaching productivity by using a unique blend of productivity metrics and STEM faculty demographics. The findings enhance our understanding of faculty roles, aiding university administrators in supporting faculty success. This insight is especially important in STEM fields, which drive technological advancement, innovation, and economic growth (Gibbs et al., 2014).

Overall, while many individual teaching and research metrics were tightly correlated with other metrics within that domain, there was little correlation between metrics across domains (Table 5). This highlights that while universities strive to support both teaching and research excellence, these goals may not be aligned within each faculty. One exception to this was a connection between research productivity metrics, including “Average citation per publication” and “Sum of grant awards” and the number of undergraduate IR mentored. This highlights that research-productive faculty may contribute to the university’s teaching mission in ways other than classroom instruction, which is typically considered the hallmark of higher education instruction. In the context of STEM student success, there has been considerable research stressing the importance of the undergraduate research experience, as participation has been correlated with increased student retention, graduation rates, continuation to graduate school, and a sense of belonging in the discipline (Morales et al., 2017; Bozeman & Corley, 2004; Lee & Bozeman, 2005; Davis & Warfield, 2011). This is particularly true for students from traditionally minoritized backgrounds (Eagan et al., 2013). So, while the C1 is characterized by high research productivity but low in LD courses, moderate in UD and GR courses, and high in IR courses for teaching productivity (Figure 1, Table 7), faculty within this cluster are contributing to the university’s teaching mission by focusing on mentoring students in undergraduate IR experiences. As high research-productive faculty may appear to be more focused on the research relative to teaching, it is important that they receive appropriate support to develop their mentorship skills to maximize the benefits of these activities for their mentees.

By clustering the eight teaching and research productivity metrics, we identified three distinct clusters of faculty. Research productivity metrics showed distinct levels across clusters as high-moderate-low, but the teaching productivity showed more complex nuances across clusters. While faculty in C1 showed a high level of research productivity, their teaching productivity levels were low in LD courses, moderate in UD and GR courses, and high in IR courses relative to faculty in the other two clusters. While faculty in C2 and C3 show higher levels of teaching productivity in LD courses than C1, they presented lower teaching productivity in UD, GR, and IR courses than C1. This complexity may help to explain why prior work has produced conflicting results, ranging from a lack of a relationship between teaching and research productivity to both synergistic and antagonistic relationships between the two domains (Cadez et al., 2017; Galbraith & Merrill, 2012; Schapper & Mayson, 2010; Becker & Kennedy, 2005; Jonker & Hicks, 2014; Fairweather, 2002; Winslow, 2010; Xu & Solanski, 2020; Keller et al., 2017; Figlio & Schapiro, 2017; Marsh & Hattie, 2002). It also emphasizes the need to include a range of metrics if we hope to gain a complete understanding of the relationship between teaching and research.

Including faculty demographic data in our analysis provided additional context to our findings. While prior work has produced conflicting results regarding the impact of gender on faculty productivity (Astin & Davis, 2019; Santo et al., 2009; Xu, 2008; Maphalala & Mpofu, 2017), gender in our sample was not predictive of which cluster a faculty might be affiliated with. Regarding discipline, Biological Sciences faculty were more likely to be found in the high research productivity cluster. This may reflect the greater availability of external funding to conduct biology-related research relative to that in other STEM fields. It may also reflect publication norms that more heavily weigh Biological Sciences journals or publications (National Science Foundation, 2020; U.S. Government Accountability Office, 2022). Similarly, it may reflect disciplinary norms related to teaching. It is documented that Biological Sciences faculty at this institution have lower teaching responsibilities than their colleagues in other STEM fields. It is also possible that either the discipline in general or the faculty specifically at this campus may place a greater emphasis on undergraduate IR mentorship. As prior work has highlighted the connection between undergraduate research experiences and faculty research productivity (Morales et al., 2017), it may be beneficial for programs to encourage their faculty to engage with students as part of the teaching mission, perhaps in exchange for other teaching responsibilities. While there is no demonstrable causal relationship between undergraduate IR mentorship and research productivity, prior work highlights that, at minimum (Brennan et al., 2019; Healey, 2005; Healey & Jenkins, 2005; Deem & Lucas, 2006), this can help to boost STEM undergraduate outcomes and help to create more inclusive academic programs.

Regarding faculty rank, our data surprisingly found that RF who were not-yet-tenured were also more likely to be found in C1. One would assume that more established faculty would exhibit higher research productivity metrics as the longer history of their research programs could positively impact their citation metrics and provide more opportunities to secure external funding. However, it is possible that more recently hired RF are conducting more cutting-edge research in their graduate and postdoctoral careers that are more connected to current research trends. Also, many funding opportunities are specifically geared toward new faculty to help get their work off the ground. This may also be influenced by lighter teaching loads that are often afforded to more recently hired faculty so that they can establish their research programs (Prince & Cotton, 2006). Regardless, it may be another signal of the growing need for institutions and funding agencies to support mid-career and later-career faculty research (Baker & Manning, 2021).

In terms of faculty position type, our data also enabled us to tease apart a small but noticeable difference between adjunct lecturers and TF in our data set. Regarding expectations, lecturers are meant to spend their time exclusively on classroom instruction, while TF at the study institution are meant to focus primarily on classroom instruction but also contribute to scholarly work and service activities (Harlow et al., 2020). Not surprisingly, both groups were overrepresented in C3, but while 25% of the lecturer population was found in C2, 50% of the TF were found in this cluster, and one of the TF was in C1. This is empirical evidence that these two faculty positions are having differential impacts. RF also have significant representation in Cluster 2, highlighting the substantial overlap in productivity between research and TF. This is surprising, considering the considerable resources afforded to RF relative to TF, including start-up package and lab space (Harlow et al., 2022). As research-intensive institutions strive to support research and teaching missions in the face of greater student enrollments and dwindling financial resources, TF may be an increasingly intriguing option relative to RF and lecturers.

While this study is more comprehensive than many in this area, the metrics used to evaluate teaching and research productivity—eight for each—do not fully capture all aspects of faculty work. These metrics primarily focus on lecture courses at both undergraduate and graduate levels, neglecting laboratory and seminar courses that often entail more varied and substantial workload responsibilities. By concentrating exclusively on lecture formats and overlooking important dimensions such as administrative duties and informal educational contributions, the study potentially misses critical elements of teaching and research productivity. This exclusion might limit the study's ability to comprehensively understand the true breadth of faculty responsibilities and their impact on perceived productivity.

Moreover, many of the research metrics employed have impacts that go beyond the defined study period of 2011 to 2017. For instance, citation metrics can reflect the influence of publications released before 2011, and the effects of significant publications towards the end of the study period may not be fully realized within the citation counts yet. Additionally, external funding figures captured might relate to grants awarded based on applications written prior to 2011, complicating the temporal alignment of data and skewing interpretations of productivity within the specific study period.

The data collected represent a single, research-intensive university and, as such, may have limited generalizability across other institutional contexts. While the STEM disciplines represented in the sample are common across higher education, the TF position type is unique. While these roles, which prioritize classroom instruction but also have scholarly and/or service expectations, are becoming more prominent (Harlow et al., 2020; Bush et al., 2011), this position is more unique in that these individuals are eligible for tenure (Harlow et al., 2020). As such, the presence of this position may influence the productivity of the traditional RF and lecturers in ways that may not be observed in other educational contexts.

CONCLUSION

This study underlines the nuanced relationship between research and teaching productivity within research-intensive environments, specifically within STEM programs. Through detailed analysis employing cluster and logistic regression models, the study illuminates the diversity in faculty roles and highlights how these roles correlate with productivity metrics across different demographics. The findings suggest that while research and teaching activities are traditionally viewed as separate endeavors, there is a complex interplay where engagements in one can influence achievements in the other. Particularly, the study reveals that faculty involvement in teaching, especially in mentoring undergraduate IR, often complements their research productivity, aligning with the dual mission of research-intensive universities to foster educational and research excellence.

Moving forward, it is essential for university administrators and policymakers to consider these insights when designing policies and support systems that enhance faculty productivity. Emphasizing the development of integrated roles that efficiently balance both research and teaching could lead to more robust academic contributions and fulfilling faculty experience, both of which have the potential to impact student success. Additionally, the differentiated impacts observed across various faculty demographics call for tailored approaches that recognize and nurture the unique contributions of diverse faculty groups, thereby promoting an inclusive academic environment that thrives on educational and research innovations.

References

Astin, H. S., & Davis, D. E. (2019). Research productivity across the life and career cycles: Facilitators and barriers for women. In *Scholarly writing and publishing* (pp. 147-160). Routledge.

Bak, H. J., & Kim, D. H. (2015). Too much emphasis on research? An empirical examination of the relationship between research and teaching in multitasking environments. *Research in Higher Education, 56*, 843-860.

Baker, V., & Manning, C. (2021). Preparing the next generation of institutional leaders: Strategic supports for mid-career faculty. To Improve the Academy: A Journal of Educational Development, 40(1). doi: https://doi.org/10.3998/tia.963

Balam, E. M., & Shannon, D. M. (2010). Student ratings of college teaching: A comparison of faculty and their students. *Assessment & Evaluation in Higher Education, 35*(2), 209-221.

Bampton, T. (2017). *Behind the Seen: Understanding academic work on the neoliberal stage.* State University of New York at Buffalo.

Becker, W. E., & Kennedy, P. E. (2005). Does teaching enhance research in economics? *American Economic Review, 95*(2), 172-176.

Bedggood, R. E., & Donovan, J. D. (2012). University performance evaluations: what are we really measuring? *Studies in Higher Education, 37*(7), 825-842.

Benton, S. L., & Cashin, W. E. (2013). Student ratings of instruction in college and university courses. In *Higher education: Handbook of theory and research: Volume 29* (pp. 279-326). Dordrecht: Springer Netherlands.

Bhattacharjee, A., & Kharade, J. (2018). Cluster-Then-Predict and Predictive Algorithms (Logistic Regression). *International Journal of Computer Sciences and Engineering, 6*(2), 249-252.

Blackwell, L. V., Snyder, L. A., & Mavriplis, C. (2009). Diverse faculty in STEM fields: Attitudes, performance, and fair treatment. *Journal of Diversity in Higher Education*, *2*(4), 195.

Bolitzer, L. A. (2019). What we know (and don't know) about adjunct faculty as teachers at four-year institutions. *The Review of Higher Education, 43*(1), 113-142.

Boring, A., & Ottoboni, K. (2016). Student evaluations of teaching (mostly) do not measure teaching effectiveness. *ScienceOpen Research.*

Bozeman, B., & Corley, E. (2004). Scientists' collaboration strategies: Implications for scientific and technical human capital. *Research Policy, 33*(4), 599-616.

Brennan, L., Cusack, T., Delahunt, E., Kuznesof, S., & Donnelly, S. (2019). Academics' conceptualizations of the research-teaching nexus in a research-intensive Irish university: A dynamic framework for growth & development. *Learning and Instruction*, *60*, 301-309.

Brew, A. (2010). Imperatives and challenges in integrating teaching and research. *Higher Education Research & Development, 29*(2), 139-150.

Bush, S. D., Pelaez, N. J., Rudd, J. A., Stevens, M. T., Tanner, K. D., & Williams, K. S. (2011). Investigation of science faculty with education specialties within the largest university system in the United States. *CBE—Life Sciences Education, 10*(1), 25-42.

Cadez, S., Dimovski, V., & Zaman Groff, M. (2017). Research, teaching, and performance evaluation in academia: the salience of quality. *Studies in Higher Education, 42*(8), 1455-1473.

Casad, B. J., Franks, J. E., Garasky, C. E., Kittleman, M. M., Roesler, A. C., Hall, D. Y., & Petzel, Z. W. (2021). Gender inequality in academia: Problems and solutions for women faculty in STEM. *Journal of neuroscience research*, *99*(1), 13-23.

Ceci, S. J., & Williams, W. M. (2011). Understanding current causes of women's underrepresentation in science. *Proceedings of the National Academy of Sciences, 108*(8), 3157-3162.

Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust: an R package for determining the relevant number of clusters in a data set. *Journal of statistical software, 61*, 1-36.

Davis, D. J., & Warfield, M. (2011). The importance of networking in the academic and professional experiences of racial minority students in the USA. *Educational Research and Evaluation, 17*(2), 97-113.

Deem, R., & Lucas, L. (2006). Learning about research: Exploring the learning and teaching/research relationship amongst educational practitioners studying in higher education. *Teaching in Higher Education, 11*(1), 1-18.

Dietz, J. S., & Bozeman, B. (2005). Academic careers, patents, and productivity: industry experience as scientific and technical human capital. *Research Policy, 34*(3), 349-367.

Eagan Jr, M. K., Hurtado, S., Chang, M. J., Garcia, G. A., Herrera, F. A., & Garibay, J. C. (2013). Making a difference in science education: The impact of undergraduate research programs. American educational research journal, 50(4), 683-713.

Elen, J., Lindblom-Ylänne, S., & Clement, M. (2007). Faculty development in research-intensive universities: The role of academics' conceptions on the relationship between research and teaching. *International Journal for Academic Development, 12*(2), 123-139.

Elsevier. (2024). *SciVal.* https://www.scival.com/

Fairweather, J. S. (2002). The mythologies of faculty productivity: Implications for institutional policy and decision making. *The Journal of Higher Education, 73*(1), 26-48.

Fairweather, J. S. (2005). Beyond the rhetoric: Trends in the relative value of teaching and research in faculty salaries. T*he Journal of Higher Education, 76*(4), 401-422.

Figlio, D. N., & Schapiro, M. (2017). Are great teachers poor scholars. *Evidence Speaks Reports, 2*(6), 1-7.

Figlio, D. N., Schapiro, M. O., & Soter, K. B. (2015). Are tenure track professors better teachers? *Review of Economics and Statistics, 97*(4), 715-724.

Fox, M. F. (2005). Gender, family characteristics, and publication productivity among scientists. *Social Studies of Science, 35*(1), 131-150.

Galbraith, C. S., & Merrill, G. B. (2012). Academic and work-related burnout: A longitudinal study of working undergraduate university business students. *Journal of College Student Development, 53*(3), 453-463.

Gibbs Jr, K. D., McGready, J., Bennett, J. C., & Griffin, K. (2014). Biomedical science Ph. D. career interest patterns by race/ethnicity and gender. *PloS one*, *9*(12), e114736.

Ginther, D. K., Schaffer, W. T., Schnell, J., Masimore, B., Liu, F., Haak, L. L., & Kington, R. (2011). *Race, ethnicity, and NIH research awards. Science, 333*(6045), 1015-1019.

Griffiths*, R. (2004). Knowledge production and the research–teaching nexus: The case of the built environment disciplines. *Studies in Higher education, 29*(6), 709-726.

Harlow, A. Lo, S. M., Saichaie, K., & Sato, B. K. (2020). Characterizing the University of California's tenure-track teaching position from the faculty and administrator perspectives. *PloS one, 15*(1), e0227633.

Harlow, A. N., Buswell, N. T., Lo, S. M., & Sato, B. K. (2022). Stakeholder perspectives on hiring teaching-focused faculty at research-intensive universities. *International Journal of STEM Education, 9*(1), 54.

Healey, M. (2005). Linking research and teaching to benefit student learning. *Journal of Geography in Higher Education*, *29*(2), 183-201.

Healey, M., & Jenkins, A. (2005). Supporting research informed teaching. *HERDSA News, 25*(3), 6-9.

Healey, M., Flint, A., & Harrington, K. (2016). Students as partners: Reflections on a conceptual model. *Teaching and Learning Inquiry, 4*(2), 8-20.

Hesli, V. L., & Lee, J. M. (2013). Job satisfaction in academia: Why are some faculty members happier than others? *PS: Political Science & Politics, 46*(2), 339-354.

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. John Wiley & Sons.

Jamil, M. A., & Khanam, S. (2024). Influence of one-way ANOVA and Kruskal–Wallis based feature ranking on the performance of ML classifiers for bearing fault diagnosis. *Journal of Vibration Engineering & Technologies, 12*(3), 3101-3132.

Jonker, L., & Hicks, M. (2014). *Teaching loads and research outputs of Ontario university faculty members: Implications for productivity and differentiation.* Toronto: Higher Education Quality Council of Ontario.

Kandel, S., Parikh, R., Paepcke, A., Hellerstein, J. M., & Heer, J. (2012, May). Profiler: Integrated statistical analysis and visualization for data quality assessment. In *Proceedings of the International Working Conference on Advanced Visual Interfaces* (pp. 547-554).

Keller, M. M., Neumann, K., & Fischer, H. E. (2017). The impact of physics teachers' pedagogical content knowledge and motivation on students' achievement and interest. *Journal of Research in Science Teaching, 54*(5), 586-614.

Kerr, C. (2001). The uses of the university (Vol. 29). Harvard University Press.

Kezar, A., & Maxey, D. (2014). Faculty matter: So why doesn't everyone think so. *Thought & Action, 2014*(2014), 29-44.

Lapworth, S. (2004). Arresting decline in shared governance: Towards a flexible model for academic participation. *Higher Education Quarterly, 58*(4), 299-314.

Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science, 35*(5), 673-702.

Lee, D. (2024). Exploring the determinants of research performance for early-career researchers: a literature review. *Scientometrics, 129*(1), 181-235.

Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science, 35*(5), 673-702.

Link, A. N., Swann, C. A., & Bozeman, B. (2008). A time allocation study of university faculty. *Economics of Education Review, 27*(4), 363-374.

Maphalala, M. C., & Mpofu, N. (2017). Are we there yet? A literature study of the challenges of women academics in institutions of higher education. *Gender and Behaviour, 15*(2), 9216-9224.

Marschke, R., Laursen, S., Nielsen, J. M., & Rankin, P. (2007). Demographic inertia revisited: An immodest proposal to achieve equitable gender representation among faculty in higher education. *The Journal of Higher Education, 78*(1), 1-26.

Marsh, H. W., & Hattie, J. (2002). The relation between research productivity and teaching effectiveness: Complementary, antagonistic, or independent constructs? *The Journal of Higher Education, 73*(5), 603-641.

Misra, J., Lundquist, J. H., & Templer, A. (2012, June). Gender, work time, and care responsibilities among faculty 1. In *Sociological Forum* (Vol. 27, No. 2, pp. 300-323). Oxford, UK: Blackwell Publishing Ltd.

Monroe, S. R., Kumar, R., & Hailemichael, A. (2012). Aksum University (AKU) faculties' needs for support in training and academic research: a basis for improvement in productivity of publication. *Ethiopian Journal of Business and Economics (The), 2*(2), 34-65.

Morales, D. X., Grineski, S. E., & Collins, T. W. (2017). Increasing research productivity in undergraduate research experiences: Exploring predictors of collaborative faculty–student publications. *CBE—Life Sciences Education, 16*(3), ar42.

Morling, B., & Lee, J. M. (2020). Are "Associate Professors" better than "Associate Teaching Professors"? Student and faculty perceptions of faculty titles. *Teaching of Psychology, 47*(1), 34-44.

National Science Foundation. (2020). *Publication output by field of science*. Retrieved from https://ncses.nsf.gov/pubs/nsb20206/publication-output-by-field-of-science

Ostertagova, E., Ostertag, O., & Kováč, J. (2014). Methodology and application of the Kruskal-Wallis test. *Applied mechanics and materials, 611*, 115-120.

Palali, A., Van Elk, R., Bolhaar, J., & Rud, I. (2018). Are good researchers also good teachers? The relationship between research quality and teaching quality. *Economics of Education Review, 64*, 40-49.

Penny, A. R. (2003). Changing the agenda for research into students' views about university teaching: Four shortcomings of SRT research. *Teaching in Higher Education, 8*(3), 399-411.

Pinheiro, D., Melkers, J., & Youtie, J. (2014). Learning to play the game: Student publishing as an indicator of future scholarly success. *Technological Forecasting and Social Change, 81*, 56-66.

Price, J., & Cotten, S. R. (2006). Teaching, research, and service: Expectations of assistant professors. *The American Sociologist, 37*(1), 5-21.

Prince, M. J., Felder, R. M., & Brent, R. (2007). Does faculty research improve undergraduate teaching? An analysis of existing and potential synergies. *Journal of Engineering Education, 96*(4), 283-294.

Rawn, C. D., & Fox, J. A. (2018). Understanding the work and perceptions of teaching focused faculty in a changing academic landscape. *Research in Higher Education, 59*, 591-622.

Robert, J., & Carlsen, W. S. (2017). Teaching and research at a large university: Case studies of science professors. *Journal of Research in Science Teaching, 54*(7), 937-960.

Rozhenkova, V., Snow, L., Sato, B. K., Lo, S. M., & Buswell, N. T. (2023). Limited or complete? Teaching and learning conceptions and instructional environments fostered by STEM teaching versus research faculty. *International Journal of STEM Education, 10*(1), 51.

Santo, S. A., Engstrom, M. E., Reetz, L., Schweinle, W. E., & Reed, K. (2009). Faculty productivity barriers and supports at a school of education. *Innovative Higher Education, 34*, 117-129.

Schapper, J., & Mayson, S. E. (2010). Research-led teaching: Moving from a fractured engagement to a marriage of convenience. *Higher Education Research & Development, 29*(6), 641-651.

Scott, G., & Danley-Scott, J. (2015). Two loops that need closing: Contingent faculty perceptions of outcomes assessment. *The Journal of General Education, 64*(1), 30-55.

Shayne, S. (2019). An exploration of adjunct faculty experiences [Doctoral dissertation, Northeastern University]. ProQuest Dissertations Publishing. (ProQuest Number: 13900621)

Schimanski, L. A., & Alperin, J. P. (2018). The evaluation of scholarship in academic promotion and tenure processes: Past, present, and future. *F1000Research, 7.*

Shin, J., & Cummings, W. (2010). Multilevel analysis of academic publishing across disciplines: Research preference, collaboration, and time on research. *Scientometrics, 85*(2), 581-594.

Singh, D. K., & Stoloff, D. L. (2003). Mentoring Faculty of Color.

Sinha, E., Massy, W. F., Mackie, C., & Sullivan, T. A. (Eds.). (2013). *Improving measurement of productivity in higher education.* National Academies Press.

Stenerson, J., Blanchard, L., Fassiotto, M., Hernandez, M., & Muth, A. (2010). The role of adjuncts in the professoriate. Peer Review, 12(3), 23-26. Retrieved from https://www.proquest.com/scholarly-journals/role-adjuncts-professoriate/docview/758939374/se-2

Swann, C. A., & Bozeman, B. (2008). A time allocation study of university faculty. *Economics of Education Review, 27*(4), 363-374.

Uttl, B., White, C. A., & Gonzalez, D. W. (2017). Meta-analysis of faculty's teaching effectiveness: Student evaluation of teaching ratings and student learning are not related. *Studies in Educational Evaluation, 54*, 22-42.

Webber, K. L., Nelson Laird, T. F., & BrckaLorenz, A. M. (2013). Student and faculty member engagement in undergraduate research. *Research in Higher Education, 54*, 227-249.

White-Lewis, D. K., Bennett, J. C., & Redd, K. (2022). Framing the Dialogue for Systemic Equity Reform in STEM Faculty Careers. *Association of Public and Land-grant Universities*.

Winslow, S. (2010). Gender inequality and time allocations among academic faculty. *Gender & Society, 24*(6), 769-793.

Xu, D., & Solanki, S. (2020). Tenure-track appointment for teaching-oriented faculty? The impact of teaching and research faculty on student outcomes. *Educational Evaluation and Policy Analysis, 42*(1), 66-86.

Xu, Y. J. (2008). Gender disparity in STEM disciplines: A study of faculty attrition and turnover intentions. *Research in Higher Education, 49*, 607-624.

Zabaleta, F. (2007). The use and misuse of student evaluations of teaching. *Teaching in Higher Education, 12*(1), 55-76.

Appendix A.

Definition of Research Productivity (RP) and Teaching Productivity (TP) Metrics.

Productivity Metrics	**Abbreviation**	**Definition**	**Data Source**
Research			
Average citation count	RP1	Average number of citations during the study period	SciVal
Average citation per publication	RP2	Average number of citations per publication during the study period	SciVal
Average field-weighted citation impact	RP3	The average ratio of citations received relative to the expected world average for the subject field, publication type and publication year, averaged over the study period	SciVal
Average h-index	RP4	A measure of both the productivity and citation impact of an entity, based on the number of publications as well as the number of citations they have received, averaged over the study period	SciVal
Average top 10% citation percentile	RP5	Average number of publications of a researcher that are highly cited, having reached a threshold (top 10%) of citations received	SciVal
Average publication top 10 citescore	RP6	Average number of publications of a selected entity that have been published in the world's top journals	SciVal
Average scholarly outcome	RP7	Average number of publications in the study period	SciVal
Sum of grant awards ($)	RP8	The total amount of grant dollars awarded during the study period	Institution
Teaching			
Average enrollment LD	TP1	Average number of enrollments per lower division course	Institution
Average enrollment UD	TP2	Average number of enrollments per upper division course	Institution
Average enrollment IR	TP3	Average number of independent research undergraduate enrollments per term	Institution
Average enrollment GR	TP4	Average number of enrollments per graduate course	Institution

Total LD courses	TP5	Total number of lower division courses taught	Institution
Total UD courses	TP6	Total number of upper division courses taught	Institution
Total IR terms	TP7	Total number of terms mentoring undergraduate students in independent research	Institution
Total GR courses	TP8	Total number of Graduate courses taught	Institution

Appendix B.

Descriptive Statistics of Faculty Teaching and Research Productivity Attributes

	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	271.8 (743.4)	83.6 (0-8820)	228.9 (17.0-245.9)
(RP2) Average citation per publication	38.0 (85.6)	22.4 (0-1762.3)	37.5 (8.0-45.5)
(RP3) Average field-weighted citation impact	1.8 (3.5)	1.3 (0.0-75.0)	1.6 (0.6-2.2)
(RP4) Average h-index	27.2 (22.5)	24.0 (0.0-132.0)	27 (11.0-38.0)
(RP5) Average top 10% citation percentile	20.9 (22.0)	14.8 (0.0-140.3)	35.7 (0.0-35.7)
(RP6) Average publication top 10 citescore	43.0 (32.0)	47.1 (0.0-175.7)	58.6 (11.1-69.7)
(RP7) Average scholarly outcome	4.9 (8.9)	3.1 (0.0-124.3)	5.2 (0.9-6.1)
(RP8) Sum of grant awards ($)	2,065,708 (3,822,680)	799,999 (0-37,832,465)	2,655,670 (56,000-2,711,670)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	95.3 (111.7)	62.0 (0.0-450.0)	149.0 (0.0-149.0)
(TP2) Average enrollment UD	49.1 (53.8)	33.0 (0.0-332.2)	58.3 (11.7-70)
(TP3) Average enrollment IR	1.3 (2.5)	0.0 (0.0-29.5)	1.8 (0.0-1.8)
(TP4) Average enrollment GR	12.4 (11.5)	10.7 (0.0-86.5)	13 (4.5-17.5)
(TP5) Total LD courses	5.8 (11.2)	2.0 (0.0-112.0)	7.0 (0.0-7.0)
(TP6) Total UD courses	6.2 (7.6)	4.0 (0.0-87.0)	8.0 (1.0-9.0)
(TP7) Total IR terms	6.0 (10.0)	0.0 (0.0-56.0)	9.0 (0.0-9.0)
(TP8) Total GR courses	5.2 (5.0)	4.0 (0.0-23.0)	7.0 (1.0-8.0)

Appendix C

Descriptive Statistics of Faculty Teaching and Research Productivity Attributes by Cluster

	Cluster 1		
	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	525.1 (1109.8)	231.4 (30-8820)	344.0 (107-451)
(RP2) Average citation per publication	64.4 (126.3)	42.1 (4.9-1762.3)	45.2 (27-72.2)
(RP3) Average field-weighted citation impact	2.7 (5.2)	2.0 (0.6-75)	1.4 (1.4-2.8)
(RP4) Average h-index	40.7 (22.7)	34.0 (1.0-132.0)	25.0 (26.0-51.0)
(RP5) Average top 10% citation percentile	34 (20.6)	29.8 (0.0-140.3)	30.0 (18.1-48.1)
(RP6) Average publication top 10 citescore	58.3 (24.4)	60.4 (0.0-175.7)	30.3 (45-75.3)
(RP7) Average scholarly outcome	8.1 (12.6)	5.4 (0.1-124.3)	5.5 (3.1-8.6)
(RP8) Sum of grant awards ($)	2,970,926 (4,346,566)	1,871,338 (0-33,357,468)	3,156,291 (623,722-3,780,013)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	71.8 (118.4)	0.0 (0.0-450.0)	123.3 (0.0-123.3)
(TP2) Average enrollment UD	52.1 (55.6)	35.4 (0.0-289.0)	66.8 (10-76.8)
(TP3) Average enrollment IR	1.9 (2.7)	1.3 (0.0-28.0)	2.7 (0-2.7)
(TP4) Average enrollment GR	11.7 (10.6)	10.3 (0.0-65.0)	12.7 (4-16.7)
(TP5) Total LD courses	2.4 (4.5)	0.0 (0.0-28.0)	3.0 (0.0-3.0)
(TP6) Total UD courses	5.9 (5.6)	5.0 (0.0-29.0)	8.0 (1.0-9.0)
(TP7) Total IR terms	10.1 (11.6)	6.0 (0.0-44.0)	18.0 (0.0-18.0)
(TP8) Total GR courses	5.5 (5.4)	4.0 (0.0-21.0)	8.0 (1.0-9.0)

	Cluster 2		
	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	154.6 (249.0)	57.6 (0-1771.3)	128.1 (25.5-153.6)
(RP2) Average citation per publication	29.7 (35.4)	20.2 (0-362.9)	24.3 (10.2-34.5)
(RP3) Average field-weighted citation impact	1.6 (1.4)	1.1 (0.0-10.5)	1.1 (0.8-1.9)
(RP4) Average h-index	25.6 (16.5)	22.0 (1.0-92.0)	19.0 (14.0-33.0)
(RP5) Average top 10% citation percentile	17.8 (19.8)	10.7 (0.0-100.0)	29.7 (0.0-29.7)
(RP6) Average publication top 10 citescore	47.6 (28.7)	49.1 (0.0-100.0)	45.9 (24.8-70.7)
(RP7) Average scholarly outcome	4.1 (4.4)	2.9 (0.0-30.0)	4.2 (1.1-5.3)
(RP8) Sum of grant awards ($)	1,683,831 (3,003,146)	617,804 (0-31,855,821)	2,242,505 (55,250-2,297,755)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	119.2 (107.8)	92.7 (0.0-445.0)	139.1 (38.7-177.8)
(TP2) Average enrollment UD	48.7 (51.3)	32.9 (0.0-332.2)	45.0 (15.4-60.4)
(TP3) Average enrollment IR	1.0 (2.6)	0.0 (0.0-29.5)	1.2 (0.0-1.2)
(TP4) Average enrollment GR	14.2 (11.1)	12.2 (0.0-58.0)	12.6 (7.4-20)
(TP5) Total LD courses	6.6 (8.0)	4.0 (0.0-49.0)	7.8 (1.0-8.8)
(TP6) Total UD courses	6.7 (7.6)	5.0 (0.0-64.0)	7.0 (2.0-9.0)
(TP7) Total IR terms	4.1 (8.8)	0.0 (0.0-56.0)	3.8 (0.0-3.8)
(TP8) Total GR courses	5.8 (4.6)	5.0 (0.0-23.0)	6.0 (2.0-8.0)

	Cluster 3		
	Mean (SD)	**Median (Min-Max)**	**IQR (Q1-Q3)**
Research Productivity Metrics			
(RP1) Average citation count	1.8 (4.5)	0.0 (0.0-27.0)	0.0 (0.0-0.0)
(RP2) Average citation per publication	1.0 (2.3)	0.0 (0.0-11.0)	0.0 (0.0-0.0)
(RP3) Average field-weighted citation impact	0.1 (0.3)	0.0 (0.0-1.1)	0.0 (0.0-0.0)
(RP4) Average h-index	2.2 (3.7)	1.0 (0.0-19.0)	2.8 (0.0-2.8)
(RP5) Average top 10% citation percentile	0.0 (0.0)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
(RP6) Average publication top 10 citescore	0.0 (0.0)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
(RP7) Average scholarly outcome	0.2 (0.6)	0.0 (0.0-3.7)	0.1 (0.0-0.1)
(RP8) Sum of grant awards ($)	1,015,973 (3,929,784)	0 (0-37,832,465)	689,691 (0-689,691)
Teaching Productivity Metrics			
(TP1) Average enrollment LD	90.4 (94.4)	92.2 (0.0-347.6)	127.6 (0.0-127.6)
(TP2) Average enrollment UD	43.8 (55.4)	29.3 (0.0-290.0)	59.6 (0.0-59.6)
(TP3) Average enrollment IR	0.4 (1.0)	0.0 (0.0-5.0)	0.0 (0.0-0.0)
(TP4) Average enrollment GR	9.7 (13.6)	6.6 (0-86.5)	14.6 (0.0-14.6)
(TP5) Total LD courses	11.4 (21)	4.0 (0.0-112.0)	11.5 (0.0-11.5)
(TP6) Total UD courses	5.9 (10.7)	2.5 (0.0-87.0)	6.8 (0.0-6.8)
(TP7) Total IR terms	1.4 (4.4)	0.0 (0.0-31.0)	0.0 (0.0-0.0)
(TP8) Total GR courses	3.0 (4.4)	1.0 (0.0-20.0)	4.0 (0.0-4.0)