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Unpacking Research Impact in Agricultural Education: Implications for Role Perception and Career Advancement

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Abstract

This study investigates research impact and academic rank progression within agricultural education disciplines, employing metrics such as the h-index, i10 index, and total citations. Grounded in Vroom's expectancy theory, the research emphasizes the significance of role perception and instrumentality in motivating faculty toward research impact and career advancement. The study collected data from publicly available Google Scholar profiles of 126 AAAE members, spanning the ranks of assistant, associate, and full professors. Mean total citations were 120.81 (SD = 110.27) for assistant professors, 685.78 (SD = 682.10) for associate professors, and 1800.63 (SD = 1315.75) for professors. Mean h-index values were 5.00 (SD = 3.03), 11.72 (SD = 4.51), and 19.86 (SD = 6.81), respectively. Forward subset regression with leave-one-out cross-validation and forward subset logistic regression minimizing AIC were used to identify factors influencing research impact and academic rank transitions. Years since first publication (YSFP), faculty size, R1 status, and disciplinary focus predicted research impact. Logistic regression models showed YSFP was the only significant variable associated with both rank transitions. These results describe relationships between experience, institutional resources, and sub-disciplinary involvement in shaping research impact and career progression.

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Introduction and Problem Statement

Research productivity and impact have long been standard metrics in faculty members' hiring, promotion, and tenure processes (Kotrlik et al., 2002; Moher et al., 2018). Schimanski and Alperin (2018) noted the significance of research productivity in personnel decisions has increased over time. Additionally, research productivity has been a key indicator of the academic prestige of researchers, institutions, and academic disciplines (Birkenholz & Simonsen, 2011; Burris, 2004; Lindner et al., 2020).

Traditionally, researchers evaluated research productivity based on the number of publications authored (Kotrlik et al., 2002); however, many institutions have begun prioritizing impact factor metrics such as the h-index and i10 index to quantify the reach and influence of researchers' work (Moher et al., 2018; Schimanski & Alperin, 2018). The h-index measures the impact of a researcher's publications based on the number of citations received and is defined as the highest number of publications of a scientist that received h or more citations (Schreiber, 2008). The i10 index, specific to Google Scholar, quantifies the number of articles a researcher has published that have been cited at least 10 times.

While these metrics offer a means of assessing research impact, their interpretation can be challenging without an appropriate baseline for comparison. This challenge is particularly relevant as our disciplines refine research impact (The American Association for Agricultural Education [AAAE], 2023) amid shifting institutional expectations (Stein, 2023). Faculty often navigate complex roles, balancing research with substantial teaching, service, and, in some cases, extension, yet are assessed using metrics whose meaning is ambiguous without appropriate baselines (Alvarez Jr., 2020; Lindner et al., 2020; Love et al., 2022; Sorcinelli, 2007). Therefore, the problem addressed in this study is the absence of grounded, discipline-specific benchmarks for interpreting h-Index, i10 index, and citation counts across academic ranks in the agricultural education disciplines. To address this gap, we examined research impact using these indicators across assistant, associate, and full professor ranks.

Theoretical and Conceptual Framework

For faculty navigating the promotion and tenure process, unclear benchmarks for research impact, inconsistent institutional expectations, and the laden pressures of service highlight the need for a framework that explains faculty members' motivation for career advancement (Birkenholz & Simonsen, 2011; Jackson et al., 2017; Moher et al., 2018). Accordingly, to explain how perceived expectations and reward pathways shape effort and advancement, we drew on Vroom's (1964) expectancy theory. According to Vroom, motivation has three influences, expectancy, instrumentality, and valence. Expectancy is a person's judgment that increased effort will result in increased performance. Instrumentality is the belief that increased performance will result in a desired outcome while valence is the importance an individual place on that outcome. Porter and Lawler (1968) later added role perception as to the theory to help capture whether people know what truly counts as successful performance. Role perception therefore describes the actions one must take, and the standards one must meet, to achieve desired outcomes.

Role perception and instrumentality were particularly relevant for this study. Instrumentality assesses whether enhancing individual research metrics, such as h-index, i10 index, or citation counts, is worth pursuing and will be acknowledged and rewarded by an individual's institution and discipline. Specifically, understanding research impact benchmarks at different academic ranks, such as assistant, associate, and full professor, can help faculty align efforts with the expectations for advancement. Further, by examining the distribution of h-indexes, i10 indexes, and total citations within our agricultural education disciplines, this study provides a clearer picture of where faculty currently stand within their academic rank and what functional goals and standards can be expected moving forward, building role perception within our disciplines. With greater role perception, faculty members can make better informed decisions about allocating their time, engaging in research, and pursuing professional development opportunities.

The application of expectancy theory to research impact data can contribute to our understanding of faculty motivation and career advancement. Further, it can offer tangible guidance for faculty, administrators, and the discipline in navigating the evolving landscape of research impact in academic careers.

Purpose

The purpose of this study was to examine research impact within agricultural education disciplines using the h-index, i10 index, and total citations across academic ranks. The findings from this study have the potential to provide faculty members with actionable benchmarks to evaluate their own research trajectories and situate their progress within broader disciplinary expectations. In alignment with expectancy theory, these models can serve as tools to clarify role perceptions and help faculty understand how their scholarly efforts may translate into career advancement. The following research objectives guided the study:

1. Compare faculty publication metrics (h-index, i10 index, and total citations) across academic ranks.
2. Determine what factors have the greatest predictive influence on research impact.
3. Determine what factors have the greatest predictive influence in distinguishing between academic ranks.

Methods

We identified all AAAE members listed in the online directory who had public Google Scholar profiles (AAAE, n.d.). For the purposes of this study, the target population was defined as tenure-track faculty holding the academic ranks of assistant, associate, or full professor. Individuals not listed as one of these ranks was excluded from the search and subsequent analysis. Our search yielded profiles for 37 assistant, 46 associate, and 42 professors (n = 126).

We determined professorial ranks and faculty size by consulting university websites and recorded each member's metrics from their Google Scholar profile, including the h-index, i10 index, and total citations. We note that Google Scholar's accuracy depends on automated matching and author curation, which can introduce omissions or misattributions; therefore, these metrics should be interpreted as best-available estimates (López-Cózar et al., 2014; Sauvayre, 2022). For Research Objective 1, we described each metric by academic rank using the mean, standard deviation, and confidence intervals.

We selected variables for Objectives 2 and 3 based on open-access availability and prior evidence on antecedents of faculty productivity and evaluation. Career stage (Years Since First Publication) is a well-established driver of output and advancement (Chen et al., 2006; Tien & Blackburn, 1996). Further, departmental capacity and university research expectations (Faculty Size, R1) worked to capture how resources and collaboration structures are linked to higher impact (Birkenholz & Simonsen, 2011; Bland et al., 2005; Jamali et al., 2016; Lee & Bozeman, 2005; McGill & Settle, 2012). Disciplinary home and AAAE regional context (AGED, Region) were used to explore the impact of regional expectations and norms. Gender was included to gauge impact of documented disparities in impact and promotion (John et al., 2016; Love et al., 2022). Collectively, these variables index institutional and experiential factors that shape role perception and the perceived instrumentality of research efforts, aligning with our expectancy-theory lens (Porter & Lawler, 1968; Vroom, 1964).To minimize variations in cited works, we collected data during two specific time periods: October 14–15, 2023, and December 27–28, 2024.

Table 1

Variables and Coding Used in this Study

Variable	Description
h-index	Number of *h* papers cited *h* times
i10 index	Number of papers cited 10 times
Total Citations	Cumulative number of citations across all manuscripts
Total Citations Per Year	Total cumulative citations divided by years since first publication
Years Since First Publication	Total years since first publication or PhD dissertation
Gender	Coded as 1 = Male, 0 = Female
Region	Coded by AAAE region; 1 = Yes, 0 = No
Discipline (AGED)	Coded as 1 = Agricultural Education, 0 = Other
R1 Institution (R1)	Coded as 1 = Yes, 0 = No
Academic Rank	Each rank coded as 1 = Yes, 0 = No
Δ h-index	Change in h-index from Oct. 2023 to Dec. 2024
Δ i10 index	Change in i10 index from Oct. 2023 to Dec. 2024
Δ Total Citations	Change in Total Citations from Oct. 2023 to Dec. 2024
Faculty Size	Total number of faculty within the department

For Objective 2, we applied forward subset regression with leave one out cross validation (LOOCV) to predict each impact metric, selecting models that minimized LOOCV mean squared error (Derksen & Keselman, 1992; James et al., 2013; Liu & Motoda, 2007). For Objective 3, we used forward logistic subset selection with the Akaike Information Criterion (AIC) to distinguish (a) assistant vs. associate and (b) associate vs. professor, evaluating performance via confusion matrices (James et al., 2013; Singh et al., 2021).

Our convenience sample of public Google Scholar profiles (n = 126) limits generalizability and may introduce self selection bias. Open access data excluded potentially relevant predictors (Jackson et al., 2017; Sinclair et al., 2014; Wilsdon, 2015). Finally, the subset selection methodology explicitly aims to maximize predictive capacity (Draper & Smith, 1966; James et al., 2013) rather than facilitate traditional hypothesis testing. Thus, our analysis focuses on identifying predictors that provide the best model fit.

Findings

Our faculty sample was nearly gender balanced, with 51.6% male and 48.4% as female. A majority of faculty (64.3%, n = 81) had agricultural education as their primary discipline, and 84.1% (n = 106) were affiliated with a R1 institution. The average faculty size was 15 members (SD = 10.98). Table 2 summarizes the universities included, number of faculty from each institution with Google Scholar profiles, and corresponding R1 Carnegie Classifications (American Council on Education, n.d.) within the sample.

Assessing our first objective, Table 3 presents the means, standard deviations, and 95% confidence intervals for each scholarly metric by academic rank. The data revealed clear and substantial increases in research impact across ranks, with distinct and well-defined demarcations observed. Notably, the 95% confidence intervals for the i10 index, h-index, total citations, and years since first publication did not overlap between ranks, indicating statistically significant differences ($p < .05$). Additionally, significant differences ($p < .05$) were evident between assistant and associate ranks for i10 Index change and total citations change. However, overlap in the 95% confidence intervals was observed for citations per year, i10 index change, and total citations change between associate and professor ranks. Furthermore, h-index change showed an overlap across all ranks.

Table 2

Universities, Faculty with Google Scholar Profiles, and Carnegie R1 Classifications

University	Faculty with Google Scholar Profiles (*n*)	R1 Status (2021)
Auburn University	2	Yes
California State University, Fresno	1	No
Clemson University	2	Yes
Illinois State University	1	No
Iowa State University	6	Yes
Kansas State University	1	Yes
Louisiana State University	1	Yes
Michigan State University	1	Yes
Middle Tennessee State University	1	No
Mississippi State University	1	Yes
Montana State University	1	Yes
Murray State University	1	No
New Mexico State University	3	No
North Carolina A&T State University	1	No
North Carolina State University	3	Yes
North Dakota State University	2	No
The Ohio State University	7	Yes
Oklahoma State University	6	Yes
Oregon State University	1	Yes
The Pennsylvania State University	3	Yes
Purdue University	6	Yes
Sam Houston State University	1	No
Sul Ross State University	1	No
Tarleton State University	2	No
Texas A&M University	12	Yes
Texas A&M University–Kingsville	1	No
Texas Tech University	4	Yes
University of Arizona	4	Yes
University of Arkansas	4	Yes
University of Arkansas at Pine Bluff	1	No
University of Florida	10	Yes
University of Georgia	7	Yes
University of Idaho	1	No
University of Kentucky	2	Yes
University of Minnesota	2	Yes
University of Missouri	3	Yes
University of Nebraska	2	Yes
University of Nevada, Las Vegas	1	Yes
University of Tennessee	4	Yes
Utah State University	4	No
Virginia Polytechnic Institute and State University	6	Yes
Washington State University	1	Yes
West Virginia University	2	Yes

Note. Carnegie Classifications were updated in 2025; the classifications reported here are based on the 2021 Carnegie Basic Classification system.

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Table 3

Publication Metrics by Professorial Rank

Variable	Assistant (n = 37)				Associate (n = 46)				Professor (n = 42)			
	M	*SD*	95% *CI*		*M*	*SD*	95% *CI*		*M*	*SD*	95% *CI*	
			LL	*UL*			*LL*	*UL*			*LL*	*UL*
i10 index	3.97	3.47	2.86	5.09	15.13	10.01	12.24	18.02	38.00	23.23	30.97	45.03
h-index	5.00	3.03	4.02	5.98	11.72	4.51	10.41	13.02	19.86	6.81	17.8	21.92
Total Cit.	120.81	110.27	85.28	156.34	685.78	682.1	488.66	882.91	1800.63	1315.75	1402.67	2198.52
Years Since First Publication	4.00	1.94	3.37	4.62	12.26	5.55	10.66	13.86	23.09	7.97	20.69	25.51
Citations Per Year	34.77	37.01	22.84	46.70	53.1	61.2	35.40	70.78	75.68	58.69	57.95	93.45
Δ i10 index	1.68	1.42	1.16	2.19	3.24	2.95	2.39	4.09	4.12	3.96	2.92	5.32
Δ h-index	0.68	1.60	0.22	1.14	1.46	1.87	0.92	1.99	1.38	1.32	0.98	1.78
Δ Total Cit.	39.82	63.12	19.47	60.15	163.5	176.26	112.56	214.44	247.02	244.37	173.12	320.93

To address objective two, forward stepwise regression with leave-one-out cross-validation (LOOCV) was utilized to identify factors with the greatest combined predictive capacity on research impact (total citations, h-index, and i10 index (n = 126)). Candidate variables for this model were: years since first publication, faculty size, R1 status, AAAE regional affiliation, Agricultural Education as primary discipline, and gender.

Total Citations

Table 4 presents the results for the total citations final subset model. The model included the predictors years since first publication (YSFP), Faculty Size, Agricultural Education discipline (AGED), and R1 research institute (R1).

Table 4

Regression Results for Predictive Factors of Total Citations

Variable	Estimate (*β*)	*SE*	*t*	*p*
Intercept	-673.44	270.61	-2.489	0.014
YSFP	52.93	8.91	5.395	<0.001
Faculty Size	16.67	8.07	2.065	0.041
AGED	371.24	178.13	2.003	0.047
R1	433.12	239.53	1.807	0.072

This model explained a significant portion of variation in total citations, $F(4,121) = 15.96$, $p < .001$, $R2 = .324$. The final model yielded a LOOCV mean squared error of 845,565, corresponding to an average predictive deviation of approximately 920 citations. Compared to the null model (intercept only), which had a LOOCV error of 1,216,254, this represents a substantial improvement in predictive accuracy and generalizability.

The final regression model produced the following predictive equation for Total Citations:
Total Citations = -673.44+ YSFP (52.93) + Faculty Size (16.67) + AGED (371.24) + R1 (433.12)

i10 index

Table 5 summarizes the results for the i10 index model. The final model included the predictors YSFP, Faculty Size, R1, Male, and Southern Region. This model accounted for a significant portion of the variance in the i10 index ($F(3,122) = 15.38$, $p < 0.001$, $R2 = 0.391$). The final model had a LOOCV mean squared error of 270, corresponding to an average predictive deviation of approximately 16.85. Compared to the null model, which had a LOOCV error 405.14, representing significant improvement in predictive accuracy and generalizability.

Table 5

Regression Results for Predictive Factors of i10 index

Variable	Estimate (*β*)	*SE*	*t*	*p*
Intercept	-9.819	4.431	-2.167	0.032
YSFP	1.017	0.164	6.198	<0.001
Faculty Size	0.405	0.145	2.790	0.006
R1	6.470	4.315	1.500	0.136
Gender (Male)	4.910	3.212	1.528	0.129
Southern Region	3.520	2.971	1.185	0.239

The final regression model produced the following predictive equation for i10 index:
i10 index = -2.686 + YSFP (1.017) + Faculty Size (0.405) + R1 (6.470) + Gender (Male) (4.910) + Southern Region (3.520)

h-index

Table 6 presents the results for the h-index model. The final model included YSFP, Faculty Size, AGED, and R1. The model explained a significant portion of variation in h-index, F(4,121) = 28.77, p < .001, R2 = .488. Under leave-one-out cross-validation, the final model achieved a mean squared prediction error (MSE) of 32.84, with an average deviation of 5.73, once again showing an improved fit when compared with 60.54 for the null model.

Table 6

Regression Results for Predictive Factors of h-index

Variable	Estimate (*β*)	*SE*	*t*	*p*
Intercept	-0.175	1.683	-0.104	0.917
YSFP	0.442	0.056	7.976	<0.001
Faculty Size	0.175	0.052	3.493	<0.001
AGED	2.552	1.142	2.223	0.027
R1	2.936	1.492	1.973	0.051

Our final model yielded the following equation to predict h-index:
h-index = -0.175 + YSFP (0.442) + Faculty Size (0.175) + AGED (2.552) + R1 (2.936)

As the h-index represents the most dynamic measure of research impact, this model provides a robust measure of scholarly impact. Further, the LOOCV error parameter is lower in the h-index model than the i10 index model while having the highest R2 value of all our models, indicating this model's enhanced ability to make accurate predictions within our discipline. Taken together, the results from these three models not only highlight key predictors of research impact but also help reinforce the theoretical lens of expectancy theory. By clarifying factors that most strongly predict research impact, these findings help faculty see a direct connection between their efforts and value outcomes, strengthening the perceived instrumentality of their research activities. Similarly, clarity of benchmarks for impact supports clearer role perception by giving faculty a more concrete understanding of what is expected at different career stages and how their performance contributes to advancement.

For research objective three, forward stepwise logistic regression was used, minimizing AIC as the selection criterion to identify factors with the greatest predictive capacity for distinguishing between academic ranks. Candidate variables included: h-index, years since first publication, faculty size, R1 status, AAAE regional affiliation, Agricultural Education as primary discipline, and gender. The h-index was included as the candidate variable to represent research performance as it represents both productivity and citation impact, providing a more balanced indicator of scholarly influence when compared to total citations or the i10 index.

Assistant to Associate

Assessing what variables have the greatest combined predictive capacity in distinguishing between assistant and associate professor ranks (n = 83), final logistic regression results are presented in Table 7. The final model in the forward stepwise procedure included the predictors YSFP, R1, AGED, and h-index.

Table 7

Logistic Results for Predictive Factors to Distinguish Between Assistant and Associate

				95% *CI* for Odds Ratio		
Variable	Estimate (*β*)	*SE*	Odds Ratio	*LL*	*UL*	*p*
Intercept	-11.275	2.988	-	-	-	< 0.001
YSFP	0.951	0.282	2.588	1.490	4.497	< 0.001
AGED	2.644	1.248	14.065	1.218	162.465	0.034
R1	2.128	1.373	8.397	0.570	123.744	0.121
h-index	0.196	0.124	1.217	0.955	1.552	0.113

Further, to assess predictive accuracy, our model's confusion matrix is presented in Table 8.

Table 8

Confusion Matrix for Assistant and Associate Model

Actual/Predicted	Assistant	Associate	Accuracy
Assistant	35	2	94.59%
Associate	2	45	95.74%

This model had an overall 95.24% predictive accuracy in distinguishing between assistant and associate ranks, while performing slightly better in predicting the associate rank. Further, this model revealed the importance of YSFP and being affiliated with the AGED discipline, being statistically significant and positively impacting the likelihood of being an associate professor. h-index and R1 status were also retained in the final model. Both were positive but non-significant effects, suggesting they may relate to advancement, but their unique contributions are modest once year in the profession and disciplinary affiliation are accounted for. Further, confidence intervals for AGED and R1 were particularly wide, reflecting limited precision in these estimates and should be interpreted with caution.

Associate to Professor

When assessing the variables that have the greatest combined predictive capacity in distinguishing between the associate and professor ranks (n = 88), the final logistic regression results are presented in Table 9. The final model in the forward stepwise procedure included the predictors YSFP, h-index, Faculty Size, and North Central.

Table 9

Logistic Results for Predictive Factors to Distinguish Between Associate and Professor

				95% *CI* for Odds Ratio		
Variable	Estimate (*β*)	*SE*	Odds Ratio	*LL*	*UL*	*p*
Intercept	-8.015	1.802	-	-	-	< 0.001
YSFP	0.217	0.057	1.249	1.127	1.413	< 0.001
h-index	0.374	0.107	1.454	1.213	1.855	< 0.001
Faculty Size	-0.068	0.098	0.934	0.860	1.001	0.072
North Central	-1.392	0.916	0.248	0.035	1.343	0.128

To assess this model's predictive accuracy, its confusion matrix is presented in Table 10.

Table 10

Confusion Matrix for Associate and Professor Model

Actual/Predicted	Associate	Professor	Accuracy
Associate	40	6	86.96%
Professor	7	36	83.72%

This model had an overall 85.39% predictive accuracy in distinguishing between associate and professor ranks while performing slightly better in predicting the associate rank. These results illustrate the slightly more complicated nature of distinguishing between associate to professor ranks when compared to assistant to associate. In this model, YSFP and h-index are strong predictors of promotion to professor, illustrating the impact of experiences and sustained scholarly impact. Conversely, the negative association between Faculty Size and North Central, though not significant, reflects the nuance of the interpretation of these models. It is unclear whether these negative associations reflect that these factors have direct negative implications or if they provide balance to the other factors in the model due to collinearity, illustrating a limitation of our methodology.

Conclusions, Discussion, and Recommendations

While Google Scholar provides a practical source for examining scholarly output and research impact, its indexing and data quality have recognized limitations (López-Cózar et al., 2014; Sauvayre, 2022). Still, the present findings show how these metrics can guide the use of research impact indicators, provide a model for future studies regarding research impact, and offer insights into the development of role expectancy within our disciplines (Porter & Lawler, 1968; Vroom, 1964). By quantifying progression in research impact (h-index, i10 index, total citations) across ranks, this study offers faculty and administrators clearer reference points for evaluating scholarly trajectories. Our analysis revealed clear progression in research impact (h-index, i10 index, total citations) across ranks. However, annual impact metrics (yearly changes in i10 index, citations, h-index, and total citations per year) overlapped confidence intervals, indicating they offer a more nuanced comparison of scholarly performance between ranks. The consistent overlap in annual h-index changes further demonstrates the complexity in setting distinct research impact expectations.

Regression analyses identified several consistent predictors of research impact: Years Since First Publication (YSFP), Faculty Size and R1 institutions significantly impacted total citations, i10 index, and h-index. Being primarily in the Agricultural Education (AGED) sub-discipline increased total citations and h-index scores. These results show how institutional resources, collaboration, and disciplinary focus contribute to scholarly output and help shape role perception and the perceived instrumentality of research investment (Bland et al., 2005; Jackson et al., 2017; Jamali et al., 2016; Porter & Lawler, 1968; Vroom, 1964).

Rank-progression analysis continues to sharpen this picture. For assistant to associate, Years Since First Publication (YSFP) and AGED were significant positive predictors, while h-index and R1 were positive but not significant; given the wide CIs for AGED and R1, these effects should be interpreted cautiously. For associate to professor, YSFP and h-index were significant and positive, indicating that time in the field and a sustained, cumulative citation record carry the greatest weight at senior promotion. Conversely, Faculty Size and North Central entered as negative, non-significant predictors, improving model fit but pointing to contextual complexity rather than simple linear relationships between setting and advancement. The differing predictor profiles across academic ranks highlights early advancement aligns more with time-in-field and disciplinary context (YSFP, AGED), whereas senior promotion emphasizes a sustained, cumulative citation record (YSFP, h-index). Recognizing these rank-contingent expectations is essential for fair evaluation and targeted mentoring.

While the study lacks generalizability, findings help expand our understanding of the complex nature of faculty research impact and career advancement. First, YSFP emerged consistently as a key factor, emphasizing sustained importance of commitment to research throughout faculty careers. Second, variables such as Faculty Size and R1 affiliations reinforce the critical role institutional context plays in impact (Bonn & Bouter, 2023; Jackson et al., 2017). Third, the unique impact patterns of AGED faculty suggest distinct disciplinary strengths that could be drawn upon to enhance broader sub-disciplinary research development.

Despite statistically significant predictors, our models explained only a moderate portion of impact variance with relatively high prediction errors, signaling potential overfitting (Hastie et al., 2009). This suggests the presence of influential but unmeasured factors such as teaching loads, service engagement, and intangible scholarly impacts (Kotrlik et al., 2002; Ramirez-Montoya et al., 2023; Wisdom et al., 20215). Thus, additional exploration is needed to fully understand the determinants of research impact.

Overall, findings support expectancy theory by clarifying the importance of role perceptions and instrumentality in motivating research impact and career advancement (Porter & Lawler, 1968; Vroom, 1964). By establishing baseline research metrics, this study provides faculty clearer expectations and role perceptions critical for professional growth. Future studies should incorporate other dimensions of scholarly impact, such as teaching and service engagement, to help provide a more comprehensive understanding of research impact (Hind et al., 1974; Jackson et al., 2017; Wilsdon, 2015). Additionally, examining factors uniquely driving impact within diverse agricultural education sub-disciplines could provide targeted developmental insights. Lastly, methodological approaches exploring interaction effects between predictors could further clarify impact dynamics. Nevertheless, this study contributes foundational insights into research impact metrics, offering clarity about professional expectations and informing faculty research development strategies aimed at career advancement within the agricultural education disciplines.

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References

American Association for Agricultural Education. (n.d.). *Member directory*. https://aaaeonline.org/directory

American Association for Agricultural Education. (2023). *AAAE research values*. https://aaaeonline.org/National-Research-Values

American Council on Education. (n.d.). *2021 basic classification*. Carnegie Classification of Institutions of Higher Education. https://carnegieclassifications.acenet.edu/2021-basic-classification

Alvarez, A. V., Jr. (2020). Learning from the problems and challenges in blended learning: Basis for faculty development and program enhancement. *Asian Journal of Distance Education, 15*(2), 112–132. https://doi.org/10.5281/zenodo.4292631

Birkenholz, R. J., & Simonsen, J. C. (2011). Characteristics of distinguished programs of agricultural education. *Journal of Agricultural Education, 52*(3), 16–26. https://doi.org/10.5032/jae.2011.03016

Blackburn, R. T., & Lawrence, J. H. (1995). *Faculty at work: Motivation, expectation, satisfaction*. Johns Hopkins University Press.

Bland, C. J., Center, B. A., Finstad, D. A., Risbey, K. R., & Staples, J. G. (2005). A theoretical, practical, predictive model of faculty and department research productivity. *Academic Medicine, 80*(3), 225–237. https://doi.org/10.1097/00001888-200503000-00006

Bonn, A., & Bouter, L. (2023). Research assessments should recognize responsible research practices: Narrative review of a lively debate and promising developments. In E. Valdés & J. A. Lecaros (Eds.), *Handbook of bioethical decisions: Volume II* (pp. 441–472). Springer. https://doi.org/10.1007/978-3-031-29455-6_27

Burris, V. (2004). The academic caste system: Prestige hierarchies in PhD exchange networks. *American Sociological Review, 69*(2), 239–264. https://doi.org/10.1177/000312240406900205

Chen, Y., Gupta, A., & Hoshower, L. (2006). Factors that motivate business faculty to conduct research: An expectancy theory analysis. *Journal of Education for Business, 81*(4), 179–189. https://doi.org/10.3200/JOEB.81.4.179-189

Derksen, S., & Keselman, H. J. (1992). Backward, forward and stepwise automated subset selection algorithms: Frequency of obtaining authentic and noise variables. *British Journal of Mathematical and Statistical Psychology, 45*(2), 265–282.

https://doi.org/10.1111/j.2044-8317.1992.tb00992.x

Draper, N., & Smith, H. (1966). *Applied regression analysis*. Wiley.

Hadjinicola, G. C., & Soteriou, A. C. (2006). Factors affecting research productivity of production and operations management groups: An empirical study. *Journal of Applied Mathematics & Decision Sciences, 2006*(2). https://emis.dsd.sztaki.hu/journals/HOA/JAMDS/Volume2006/96542.pdf

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer. https://doi.org/10.1007/978-0-387-84858-7

Heng, K., Hamid, M., & Khan, A. (2020). Factors influencing academics' research engagement and productivity: A developing countries perspective. *Issues in Educational Research, 30*(3), 965–987. https://search.informit.org/doi/abs/10.3316/informit.465283943914964

Hind, R. R., Dornbusch, S. M., & Scott, W. R. (1974). A theory of evaluation applied to a university faculty. *Sociology of Education*, 114-128. https://doi.org/10.2307/2112169

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United States of America*, *102*(46), 16569–16572. https://doi.org/10.1073/pnas.0507655102

Jackson, J. K., Latimer, M., & Stoiko, R. (2017). The dynamic between knowledge production and faculty evaluation: Perceptions of the promotion and tenure process across disciplines. *Innovative Higher Education*, *42*, 193-205. https://doi.org/10.1007/s10755-016-9378-3

Jamali, H. R., Nicholas, D., & Herman, E. (2016). Scholarly reputation in the digital age and the role of emerging platforms and mechanisms. *Research Evaluation, 25*(1), 37–49. https://doi.org/10.1093/reseval/rvv032

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). Springer. https://doi.org/10.1007/978-1-4614-7138-7

John, A. M., Gupta, A. B., John, E. S., Lopez, S. A., & Lambert, W. C. (2016). A gender-based comparison of promotion and research productivity in academic dermatology. *Dermatology Online Journal, 22*(4). https://doi.org/10.5070/D3224030651

Kotrlik, J. W., Bartlett, J. E., Higgins, C. C., & Williams, H. A. (2002). Factors associated with research productivity of agricultural education faculty. *Journal of Agricultural Education,* *43*(3), 1–10. https://doi.org/10.5032/jae.2002.03001

Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science, 35*(5), 673–702. https://doi.org/10.1177/0306312705052359

Lindner, J. R., Harder, A., & Roberts, T. G. (2020). Elevating the Impacts of Research in Agricultural Education. *Journal of Agricultural Education*, *61*(2), 249-262. https://doi.org/10.5032/jae.2020.02249

Liu, H., & Motoda, H. (Eds.). (2007). *Computational methods of feature selection*. CRC Press. https://doi.org/10.1201/9781584888796

López-Cózar, E. D., Robinson-García, N., & Torres-Salinas, D. (2014). The Google Scholar experiment: How to index false papers and manipulate bibliometric indicators. *Journal of the Association for Information Science and Technology*, *65*(3), 446-454. https://doi.org/10.1002/asi.23056

Love, H. B., Stephens, A., Fosdick, B. K., Tofany, E., & Fisher, E. R. (2022). The impact of gender diversity on scientific research teams: A need to broaden and accelerate future research. *Humanities and Social Sciences Communications, 9*(1), 1–12. https://doi.org/10.1057/s41599-022-01389-w

McGill, M. M., & Settle, A. (2012). Identifying effects of institutional resources and support on computing faculty research productivity, tenure, and promotion. *International Journal of Doctoral Studies, 7*, 167–198. https://doi.org/10.28945/1581

Moher, D., Naudet, F., Cristea, I. A., Miedema, F., Ioannidis, J. P. A., & Goodman, S. N. (2018). Assessing scientists for hiring, promotion, and tenure. *PLOS Biology, 16*(3). https://doi.org/10.1371/journal.pbio.2004089

Porter, L. W., & Lawler, E. E. (1968). *Managerial attitudes and performance*. Irwin Dorsey.

Ramirez-Montoya, M. S., Ceballos, H. G., Martínez-Pérez, S., & Romero-Rodríguez, L. M. (2023). Impact of Teaching Workload on Scientific Productivity: Multidimensional Analysis in the Complexity of a Mexican Private University. *Publications*, *11*(2), 27. https://doi.org/10.3390/publications11020027

Sauvayre R. (2022). Types of errors hiding in Google Scholar data. *Journal of Medical Internet Research*, *24*(5), e28354. https://doi.org/10.2196/28354

Schimanski, L. A., & Alperin, J. P. (2018). The evaluation of scholarship in academic promotion and tenure processes: Past, present, and future. *F1000Research, 7*, 1605. https://doi.org/10.12688/f1000research.16493.1

Schreiber, M. (2008). An empirical investigation of the g-index for 26 physicists in comparison with the h-Index, the A-index, and the R-index. *Journal of the American Society for*

Information Science and Technology, 59(9), 1513–1522. https://doi.org/10.1002/asi.20856

Sinclair, J., Cuthbert, D., & Barnacle, R. (2014). The entrepreneurial subjectivity of successful researchers. *Higher Education Research & Development, 33*(5), 1007–1019. https://doi.org/10.1080/07294360.2014.890574

Singh, P., Singh, N., Singh, K. K., & Singh, A. (2021). Diagnosing of disease using machine learning. In *Machine learning and the internet of medical things in healthcare* (pp. 89–111). Academic Press. https://doi.org/10.1016/B978-0-12-821229-5.00003-3

Sorcinelli, M. D. (2007). Faculty development: The challenge going forward. *Peer Review, 9*(4), 4–8. https://www.proquest.com/scholarly-journals/faculty-development-challenge-going-forward/docview/216587063/se-2

Stein, M. (2023). The end of faculty tenure and the transformation of higher education. *American Association of University Professors*. https://www.aaup.org/article/end-faculty-tenure-and-transformation-higher-education

Tien, F. F., & Blackburn, R. T. (1996). Faculty rank system, research motivation, and faculty research productivity: Measure refinement and theory testing. *The Journal of Higher Education, 67*(1), 2–22. https://doi.org/10.1080/00221546.1996.11780246

Vroom, V. H. (1964). *Work and motivation*. Wiley and Sons.

Williamson, I. O., & Cable, D. M. (2003). Predicting early career research productivity: The case of management faculty. *Journal of Organizational Behavior, 24*(1), 25–44. https://doi.org/10.1002/job.178

Wilsdon, J. (2015). *The metric tide*. SAGE Publications Ltd.