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Predicting Research Productivity in STEM Faculty: The Role of Self-determined Motivation

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Abstract

How are university faculty members in STEM disciplines motivated to conduct research, and how does motivation predict their success? The current study assessed how multiple types of self-determined motivation predict research productivity in a sample of 651 faculty from 10 US institutions. Using structural equation modeling, the basic psychological needs of autonomy and competence predicted autonomous motivation (enjoyment, value) that, in turn, was the strongest predictor of self-reported research productivity. Using negative binomial regression, autonomous motivation was the strongest predictor of faculty publications and citations, with a one-standard deviation increase in autonomous motivation (approximately a half response option on a 1–5 Likert scale) corresponding to an 11.63% increase in publications and a 22.57% increase in citations over a three-year period. Occupational and social-environmental background variables (e.g., research percentage on contract, career age, balance, collegiality), as well as controlled motivation (guilt, rewards), had comparatively limited predictive effects. These results are of relevance to higher education institutions aiming to support scholarly productivity in STEM faculty in identifying specific beneficial and detrimental aspects of faculty motivation that contribute to measurable gains in research activity.

Keywords Faculty · Motivation · Research productivity · Bibliometrics · STEM

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Does Self-determined Motivation Predict STEM Faculty Research Success and Productivity?

Research contributions in Science, Technology, Engineering, and Mathematics (STEM) have led to dramatic improvements in the United States (US), including "enhanced living standards and life expectancy, better access to information and connectivity across the globe, and increased access to and affordability of consumer goods" (NSB NSF, 2020a, p. 3). US science and engineering jobs are predicted to grow by 13% compared with 7% of the workforce overall (NSB NSF, 2019) indicating continued demand. However, the US share of the world STEM enterprise is dropping (37–25%) as other countries are investing more in research and development (NSB NSF, 2020b). The US is also falling behind China and the European Union in percentage of research output and rate of top 1% cited articles (NSB NSF, 2020b), despite US spending on research and development in most science and engineering fields increasing annually (NCSES, 2021). As federal funding for research is finite, examinations of other factors impacting faculty research are needed to determine how to maintain and boost STEM productivity.

Most studies to date examining predictors of faculty research productivity have focused on demographics (e.g., gender, race/ethnicity; Hoppe et al., 2019; Sugimoto et al., 2013), occupational characteristics (rank, discipline, contract research percentage, institutional type; Bentley & Kyvik, 2013; Gottlieb & Keith, 1997; Larivière et al., 2006; Stolzenberg et al., 2019), and social-environmental factors (work-life balance, clarity of expectations, collegiality, climate; Sheridan et al., 2017; Stupnisky et al., 2015). In contrast, fewer studies have examined faculty members' *motivation* to conduct research, that is, what drives or energizes them to engage in scholarship. Whereas scattered existing research on faculty motivation suggests that both the type and level of motivation faculty have for research play a vital role in their success (e.g., Stupnisky et al., 2017, 2019a), generalizations to faculty in STEM disciplines has been limited due to sampling, measurement, and analytical issues (e.g., small sample sizes, unreliable measures). To address this research gap, the current study aimed to examine the factors affecting university STEM faculty members success and productivity in research, and specifically examine the role of motivation.

Faculty Motivation for Research

Faculty members' motivation to conduct research is pivotal to their success (Daumiller, et al., 2020). Several motivation theories have been applied to faculty research (e.g., Goal Theory by Daumiller & Dresel, 2020; Social-cognitive Theory by Reyes-Cruz et al., 2018; Expectancy Theory by Chen & Zhao, 2013; Control-Value Theory of Emotions by Stupnisky et al., 2019b), yet Self-determination Theory (SDT) was chosen as the current study framework because of its clear conceptual linkages and past empirical support (Deci & Ryan, 1985; Deci et al., 1997; Ryan & Deci, 2017). SDT proposes that motivation, in this case faculty motivation for research, is determined by level of satisfaction of three basic psychological needs: competence (perceived research expertise or skill), autonomy (freedom to choose research initiatives and strategies), and relatedness (feeling connected with collaborators). SDT asserts that the *type* of motivation, driven by satisfaction of basic psychological needs, is critical to predicting behavioral outcomes in the context of faculty research (Deci & Ryan, 2008).

If these needs are optimally supported, faculty should experience intrinsic motivation, which is engaging in research because it is interesting and enjoyable. This is an ideal state as intrinsically motivated faculty would seek out research opportunities, and curiously engage in research with an inclination towards learning and mastery. Identified motivation for a faculty member is when they deem research engagement to be valuable and important. For those with high identified motivation, the basic needs are largely satisfied, including autonomy, as the faculty concurs with and "owns" the reasons for engaging in research as they see the goal as relevant and worthwhile; however, as the activity itself does not yield enjoyment it is not intrinsic. Ryan and Deci (2021) argued identified motivation becomes especially important when activities require diligence and persistence, which seems fitting for research as it often requires long-term passion and grit (Jaeger et al., 2022). In contemporary SDT, Ryan and Deci aggregated intrinsic and identified regulations into *autonomous motivation* due to their shared properties and high correlations. We hypothesized faculty whose basic needs regarding research are satisfied are more likely to experience autonomous motivation and will be more likely to successfully produce high impact scholarly work.

Not all faculty, however, are autonomously motivation for research. To the detriment of satisfying their basic psychological needs, faculty are paid to conduct research, frequently evaluated, subjected to deadlines, pressured to win grants, and sometimes interact with difficult students and colleagues. If these outside influences are emphasized, it may lead to faculty research engagement for more environmental and instrumental purposes that are characterized as *controlled motivation* (Ryan & Deci, 2021). One such type is external motivation, which involves faculty conducting research to gain rewards (e.g., merit-based salary increases, awards, recognition from others) or avoid punishment (e.g., poor annual evaluation, performance improvement plans), which can powerfully motivate short-term behaviors but will be poorly maintained when contingencies are removed. External motivation, according to SDT, often fails to produce high-quality performance as the focus is strategically on getting the reward, not the value of the activity itself. Introjected motivation is faculty research engagement based on internal pressures to preserve and boost self-esteem, or prevent guilt and shame. Although the pressure of introjected motivation is coming from within, it is still considered controlled motivation as the pressure on the self is to act or face self-evaluative consequences. We hypothesized faculty whose basic needs regarding research are less satisfied are likely to experience controlled motivation and will be less likely to successfully produce scholarly work than their more autonomous motivated counterparts. Amotivation is the total absence of motivation, characterized by faculty basic needs not being satisfied or thwarted by environmental factors resulting in a complete lack of research engagement. This is hypothesized to be the poorest motivational state for faculty research productivity.

Several early studies examining faculty motivation for research discussed and measured internal/external motivation. In the earliest study, Singh et al. (1989) surveyed 328 faculty at a major US mid-western university and found that intrinsic motivation for research, defined as "to satisfy intellectual curiosity and to derive excitement and stimulation from the research process" (p. 463), was negatively correlated with burnout, explaining 74% of the variance. Colbeck (1992) measured motivation among 1,504 US faculty with a single question that asked if their interests (i.e., intrinsic motivation) concerned primarily research or teaching. Faculty who reported greater interest in research also valued research more as a pathway to tenure (controlling for work context and demographic variables). Similarly, a survey by Barnett et al. (1998) of 1,764 faculty from 24 US medical schools found that self-reported number of publications to be positively associated with intrinsic "career motivation" and negatively correlated with extrinsic career motivation.

Support for the applicability of SDT as a theoretical framework to understand faculty motivation for research also grew through other methodologies. In a qualitative study, Walker and Fenton (2013) found 36 highly productive professors frequently attributed intrinsic motivation, characterized by fun, enjoyment, and passion, as the most important factor supporting their research productivity, more so than any other personal characteristic (e.g., time management, skills) or institutional factor (e.g., research emphasis, resources). Scale development studies also supported the applicability of SDT to faculty motivation for research. Deemer et al. (2012), as well as Leech and Haug (2016), developed the Research Motivation Scale for use with STEM faculty and psychometric tests found distinct intrinsic versus extrinsic motivation constructs; however, the scales did not align all SDT motivation types, nor did they test the motivation constructs relationships with faculty research success.

With respect to more recent quantitative studies, Hardré et al. (2011) surveyed 781 faculty members from 28 US institutions to find intrinsic motivation for research had a significant positive relationship with their perceived value of conducting research that, in turn, predicted research effort and research productivity. That study, however, did not consider the role of basic psychological needs, and the research success measure was self-reported. Following from this research, Stupnisky et al. (2017) surveyed 105 pre-tenure faculty from two Midwestern doctoral US universities and found faculty who perceived their basic psychological needs of autonomy and competence were being satisfied also tended to report higher levels of intrinsic motivation that, in turn, predicted greater perceived and expected success in research. Finally, Stupnisky et al. (2019a) studied 1846 US faculty from 19 institutions and found satisfaction of autonomy and competence needs to predict autonomous motivation (a combination of enjoyment and value) that was positively related to self-reported research productivity, beyond demographic and position details. Alternatively, motivational beliefs focused on external (rewards) and introjected motivation (guilt) had little to no relationship with self-reported research success among faculty.

There are several limitations of past studies on faculty motivation for research we sought to address in the current study. First, many early studies involved an incomplete consideration of SDT, such as examining only one motivation type (e.g., intrinsic) and not accounting for the role of the basic psychological needs. Second, many of the study samples were from disciplines where research success may be defined differently (e.g., humanities vs. STEM programs have different expectations for number of publications, grants, citations), such as faculty from exclusively teacher education (Angaiz et al., 2021), business (Chen & Zhao, 2013), or medicine (Bland et al., 2005). Also, some studies recruited faculty participants from a single institution thus limiting the generalizability of results (Fung, 2017; Singh et al., 1998; Vasil, 1992). Third, many of the studies analyses did not employ advanced statistical methods that account for measurement error (e.g., latent variables), nor did they control for critical background variables that predict research success. Finally, measures across studies raised questions of reliability and validity, with some motivation measures being one or two items (e.g., Blackburn et al., 1991; Bland et al., 2002), most measures of research success being exclusively self-report (e.g., Hardré et al., 2011; Perry et al., 2000), and multiple studies including no subjective or observable indicator of research success (e.g., Edgar & Geare, 2013; Reyes-Cruz et al., 2018).

Faculty Research Success

Definition and Measurement

Research success can be broadly defined as contributing to the scientific advancement of a scholarly field of inquiry and be recognized for it. However, operationally measuring research success is difficult for several reasons. Disciplinary and institutional differences result in most universities having detailed faculty-evaluation guidelines unique to every college, department, and program (McKiernan et al., 2019). Individual workloads must be accounted for, as some faculty spend a large percentage of their time on research, whereas others are contractually obligated to engage in more teaching and/or service. Faculty engagement in research also changes depending on the demands of a given semester or one's career stage (Laudel & Gläser, 2008; Stolzenberg et al., 2019), with some research projects taking several years to reach completion. In terms of impact, whereas some publications have a tremendous effect on a field, hundreds of other papers may make smaller yet nevertheless important contributions. Moreover, successful grant applications typically require multiple rejections, revisions, and resubmissions before funding is secured (Harris, 2021; NIH, 2021). Given the complex nature of defining what it means to achieve research success, optimal assessment measures must be robust and multi-dimensional in nature.

Faculty self-reported research success, although susceptible to reporting error, can capture research activity prior to more objective outputs needing months or years of external review before becoming public. In existing research on faculty research success, self-reported measures have typically addressed three domains: activity (e.g., time and energy on literature reviews, study design, data collection, analysis, writing, etc.), publishing (e.g., rate and number of publications), and securing external grant funding (e.g., number and dollar amount of grants received) (Stupnisky et al., 2019a). Faculty are often requested to complete such measures in relation their own self-standards, departmental standards, and other faculty in their department or field (Elliot et al., 2011; Mascret et al., 2015; Stupnisky et al., 2019a). Indeed, self-perceptions of research productivity have been found to correlate with self-reported number of articles published ($r=0.47$, $p<0.001$; Ito & Brotheridge, 2007). Mongeon et al. (2016) further showed grant funding to be related to research productivity and scientific impact, with the number of articles produced and the average relative citations increasing proportionally with funding up until a certain point where they start to decrease.

External measures of faculty research success also are complex. The field of *bibliometrics* examines patterns of authorship, publication, and literature use through the analysis of scholarly documents authored by researchers (Diodato, 1994; Sugimoto & Larivière, 2018) primarily in the fields of science and technology (Moed, 2005; van Raan, 1988). A fundamental principle of bibliometrics is that new knowledge created by scientists is embedded in the scientific literature, and that by measuring scientific literature, one measures new knowledge production, usage, as well as the context in which this knowledge is produced. Number of publications in peer-reviewed scientific journals remains a generally agreed upon indicator of STEM research productivity (Hardré et al., 2011; Ito & Brotheridge, 2007; Javitz et al., 2010; Sax et al., 2002; Walker & Fenton, 2013). Productivity should be complemented with indicators of research impact, such as citation counts (Moed, 2005). Modern bibliometrics is strongly linked with the Science Citation Index (SCI)—a precursor to the Web of Science—created in 1963 by Eugene Garfield (Wouters, 1999). It indexes references made by each source item it files allowing for the compilation of citation counts and, hence, scientific impact measures (Garfield, 1979). However, bibliometric indicators also have limitations, namely coverage: the bibliometric databases do not include publications outside of those indexed in the most prominent journals in a given field (Mongeon & Paul-Hus, 2016), meaning that some publications are never counted. Most bibliometrics also assign publications to authors irrespective of their contribution (lead author, secondary author, etc.). Finally, as a given paper may be cited for various reasons, citations counts do not always represent unbiased indicators of research impact or quality. As productivity involves subjective and objective elements, research success measures will ideally triangulate faculty self-reported levels of activity and output with externally indexed indicators of productivity and impact.

Predicting Research Success

Several faculty job characteristics have been consistently examined as factors contributing to research success. For instance, faculty rank and career age have been found to predict research productivity, with findings showing junior faculty to score lower on scholarly productivity than associate or full professors (e.g., 2016–17 Higher Education Research Institute Faculty Survey; Stolzenberg et al., 2019). In terms of time invested in research activities (i.e., research load), Gottlieb and Keith (1997) found “that as the amount of hours spent on research increases, the number of articles published during the previous three years also increases” (p. 414). Interestingly, Bentley and Kyvik (2013) showed that US faculty spend less time on research, on average, than peers across 13 other countries (17.6 hours per week vs 18.5 hours, or 35.8% vs 39% of total working hours). Institutional support was also found by Stolzenberg et al. (2019) to predict research success, with 69.2% of faculty respondents reporting adequate support for faculty development at their institution, yet only 12.8%-34.7% of faculty participating in research and grant writing workshops.

Social-environmental factors have also been studied in relation to faculty research outcomes. Balancing the competing demands for their time, both professionally among teaching/research/service and between work and home life, has been positively related to faculty job satisfaction (Beckett et al., 2015; Watanabe & Falci, 2016). Clear performance expectations, such as well-defined targets for research, conference presentations, publications, and grant applications, have also been found to contribute to research success. For instance, O’Meara et al. (2016) similarly found “unmet expectations and broken contracts shaped the departure decisions” (p. 291) of 33 faculty who had committed to or already left their institutions. Lawrence et al.’s (2014) survey of 2,247 professors found only moderate agreement ($M=3.71$, five-point scale) that their tenure review process was fair. Faculty research also benefits from collegial relationships with their coworkers, as suggested by interviews by Gonzales and Terosky (2016) with 50 faculty showing colleagueship to contribute to the effective development of one’s research and writing agenda. Despite its importance, many studies have found faculty to struggle with establishing collegiality in their research activities and experience isolation due to competition and departmental politics (Stupnisky et al., 2015; Trotman & Brown, 2005; Trower & Gallagher, 2008). While these factors have been studied predominantly among faculty regarding job satisfaction, they have rarely been considered as predictors in the research domain specifically or in comparison to faculty motivation.

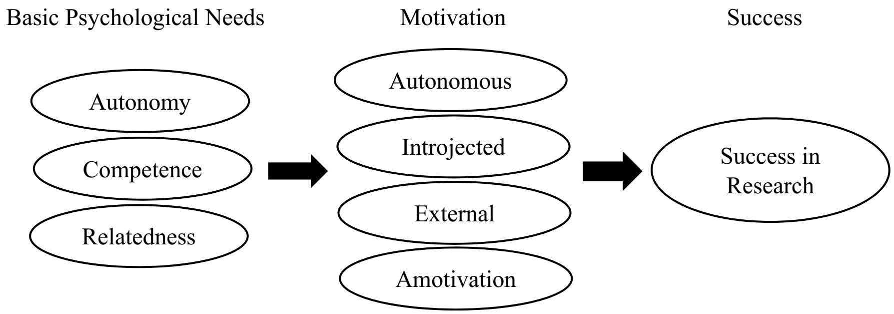


Fig. 1 Conceptual model of faculty motivation and research success

Current Study

The current study tested a conceptual model hypothesizing a central role of SDT motivation in faculty members' research success (see Fig. 1). To address gaps in prior research, this study examined all SDT basic psychological needs and motivation types, collected a large sample of STEM faculty across multiple disciplines and institutions, utilized multi-item measures of constructs including self-reported research success and bibliometric indictors of research productivity, and employed robust statistical analyses. Key research questions included: To what extent are faculty SDT basic needs satisfied (autonomy, competence, relatedness) related to faculty motivation? In what ways are faculty members typically motivated to conduct research (autonomous or controlled)? How does motivation predict faculty research success (self-reported, bibliometric)? We additionally tested the relationship of faculty motivation for research controlling for critical background characteristics (age, rank, research percentage on contract) and social-environmental factors (institution support, balance, collegiality, expectations).

Methods

Participants and Procedure

Study participants included 651 STEM faculty members recruited from 10 US Doctoral Universities (R2 Higher Research Activity Carnegie Classification) who completed a confidential online survey in February of 2020 prior to the US COVID-19 pandemic shutdown.[1] Historically R2 institutions strive for higher Carnegie Classification to gain prestige, a phenomenon known as "upward drift" (Aldersley, 1995), which may result in imbalanced faculty workloads marked by considerable teaching loads paired with high research demands (Greene et al., 2008; O'Connor et al., 2011); thus, motivation for research is highly salient. Faculty were directly emailed a link to the survey either by the researchers who received a list of STEM faculty email addresses or an administrator from their institution and given

[1] We limited our data to faculty reporting research activity and complete or nearly-complete responses to the survey, resulting in a final analyzed sample of 651 faculty. The breakout of the missing data indicated that 56 out of 821 (6.8%) had next to no data entries with most of their variables missing; 38 (4.6%) were missing the majority of data entries in the motivation and perceived success sections; 5 (0.6%) had a substantial number of variables missing; 71 participants (8.6%) had zero research percentage.

three weeks to complete it (non-completers received weekly reminders). In exchange for their participation faculty were offered entry into drawing for gift cards and a summary of the results. The study received ethical approval by the Institutional Review Board from the first author's institution.

The sample (Table 1) had approximately equivalent gender representation, reported an average age of 47.0 years ($SD = 11.0$), were mainly White, not of Hispanic/Latinx/Spanish ethnicity, and primarily born and raised in the USA (i.e., not an international faculty member). Among the participating STEM faculty members at R2 institutions, 46.9% were White males; 34.9% White females; 8.3% Asian males; 4.0% Asian females; and the remaining 5.9% were Black males and females, indicated multiple races, or preferred not to respond. For comparison, a study of degree-granting US postsecondary institutions in fall 2018 found full-time faculty to include 40 percent White males; 35 percent White females; 7 percent were Asian/Pacific Islander males; 5 percent were Asian/Pacific Islander females; and 3 percent each were Black males, Black females, Hispanic males, and Hispanic females (US Dept of Education, NCES, IPED, 2019). The similarities of the current sample with the national population of faculty suggests good potential for generalizability.

Participants were approximately evenly distributed across rank and tenure status designations, as well as a range of STEM disciplines. The average career age (time from PhD) was 13.65 years ($SD = 10.1$), and participants worked an average of 51.4 hours per week ($SD = 10.4$). Faculty reported that their contracts required the following percentages of effort/time: 40.4% research ($SD = 20.5$), 36.4% teaching ($SD = 19.4$), 12.9% service ($SD = 10.5$), and 7.5% other/administration ($SD = 16.6$).

Measures

Basic Psychological Needs

Twelve items adapted from Stupnisky et al. (2017, 2019a) measured faculty members' perceived level of psychological need satisfaction regarding their research. Following the question, "Regarding your RESEARCH, to what extent do you agree with the following?" were three four-item subscales (1 = *Strongly disagree*, 5 = *Strongly agree*): autonomy ("I have a sense of freedom to make my own choices"), competence ("I have confidence in my ability to do things well"), and relatedness ("I am supported by the people whom I care about [students, colleagues, etc.]"). Psychometrics and descriptive statistics for study measures are presented in Table 2.

SDT Motivation Types

Faculty motivation for research was measured using 12 items adapted from Stupnisky et al. (2019a). Regarding the question, "To what extent are the following reasons for why you engage in RESEARCH?" (1 = *Strongly disagree*, 5 = *Strongly agree)*, faculty responded to five three-item subscales: intrinsic ("It is enjoyable to engage in research"), identified ("My research is important to me"), positive introjected ("When I do research I feel proud of myself"), negative introjected ("I would feel guilty not engaging in research"), external motivation ("Because I am paid to produce research"), and amotivation ("Honestly, I don't know why I do research"). Exploratory factor analysis (principal axis factoring with

Table 1 Participant characteristics

		Count	Percent
Gender identity	Man	388	59.6
	Woman	255	39.2
	I prefer not to respond	8	1.2
Racial identification	White	531	81.6
	Asian	82	12.6
	Multiracial	15	2.3
	Other	11	1.7
	Black or African American	5	0.8
	No response	7	1.8
Ethnicity	Not of Hispanic, Latinx, or Spanish origin	602	92.5
	Yes, of Hispanic, Latinx, or Spanish origin	42	6.5
	No response	7	1.1
International	No	471	72.4
	Yes	176	27.0
	No response	4	0.6
Primary disciplinary area	Life sciences	178	27.3
	Social sciences	97	14.9
	Engineering	85	13.1
	Psychology	50	7.7
	Geoscience	46	7.1
	Mathematical sciences	36	5.5
	Chemistry	33	5.1
	Physics and astronomy	33	5.1
	STEM education learning research	30	4.6
	Computer and information science and engineering (CISE)	25	3.8
	Materials research	5	0.8
	No response	33	5.1
Academic rank	Assistant Professor	219	33.6
	Associate Professor	178	27.3
	Full Professor	212	32.6
	Instructor/teaching professor	9	1.4
	Research scientist/analyst	8	1.2
	Other	25	3.8
Tenure status	Tenured	376	57.8
	On tenure track but not tenured	209	32.1
	Not on tenure track	63	9.7
	Other	3	0.5

oblimin rotation) revealed the intrinsic and identified subscales are best combined to form a composite autonomous motivation subscale, consistent with past research on faculty motivation for teaching and research (Stupnisky et al., 2018, 2019a).

Table 2 Descriptive statistics and reliabilities for study scales

Measure	# items	*M*	*SD*	Range	Skew	Kurtosis	α
Basic needs							
Autonomy	4	4.11	0.66	1–5	− 0.95	1.49	.83
competence	4	4.23	0.58	1.75–5	− 0.58	0.59	.83
Relatedness	4	3.93	0.71	1–5	− 0.65	0.69	.86
Motivation							
Intrinsic	3	4.51	0.59	2–5	− 1.37	2.08	.85
Identified	3	4.40	0.59	1.67–5	− 1.17	1.70	.67
[1]Autonomous	6	4.45	0.55	2–5	− 1.27	1.92	.86
Introjected	3	3.42	1.02	1–5	− 0.46	− 0.53	.85
External	3	3.53	0.83	1–5	− 0.43	− 0.25	.61
Amotivation	3	1.86	0.84	1–5	1.14	1.21	.82
Success							
Activity	4	3.53	0.76	1–5	− 0.38	− 0.09	.81
Publication	4	3.32	0.90	1–5	− 0.28	− 0.36	.88
Grants	4	3.15	1.00	1–5	− 0.05	− 0.71	.90
[2]Perceived overall	12	3.34	0.75	1.17–5	− 0.13	− 0.09	.91
[3]Publications	1	7.75	7.13	1–33	1.50	1.80	–
Citations	1	27.20	39.71	0–225	2.42	6.55	–
Success covariates							
Career age	1	13.65	10.10	1–50	0.89	0.22	–
Research % on contract	1	40.36	20.53	0.2–100	0.59	0.51	–
Institutional support	7	2.94	0.77	1–5	0.00	− 0.26	.83
Personal balance	4	3.15	0.67	1–5	− 0.40	− 0.04	.78
Professional balance	4	3.21	0.79	1–5	− 0.19	− 0.23	.82
Clear expectations	4	3.52	0.53	1–5	− 0.79	1.75	.73
Collegiality	4	3.76	0.88	1–5	− 0.91	0.63	.83

[1]Autonomous motivation is the average of all intrinsic and identified motivation items

[2]Perceived overall is the average of activity, publication, and grant success measures

[3]Faculty with more than 33 publications ($n = 12$) and more than 233 citations ($n = 12$) were outliers and removed from analysis

Research Success

Faculty were asked to "Please rate your success over the last three academic years" in three areas: conducting research activities (e.g., literature reviews, study design, data collection, analysis, writing, etc.), publishing research, and securing external grant funding for research. Each of the three aspects of research activity was rated using four items on a five-point scale (1 = *Well below average*, 3 = *Average*, *5* = *Well above average*; Stupnisky et al., 2019a): "Your own standards", "Your department's standards for tenure and promotion", "Colleagues in your department", and "Colleagues in your field(s)".

Bibliometric indicators of faculty research publications and their citations over the three years prior to the survey were also collected from Web of Science. Survey respondents were matched with the publications indexed in the Web of Science based on their family name and first name. Then, each publication portfolio was manually curated to remove papers authored by homonyms. This was performed by finding the CVs of researchers online, as well as other heuristics such as the presence of their institution of affiliation on the paper and the proximity between the discipline of the publication and their departmental affiliation. The coverage of bibliometric databases varies by country and discipline (Mongeon & Paul-Hus, 2016); however, for US authors, the coverage of the database is quite good, given that it mostly indexes papers in English.

In both variables, outliers were identified as those scores falling outside 97.5% of all scores and were trimmed (specifically 12 faculty with more than 33 publications, and 12 faculty with more than 234 citations), however the distribution of each variable still followed a positive skew that was addressed in the analysis.

Covariates

Faculty career age and research effort percentage on contract were included in analyses as covariates. Perceived institutional support for research was measured using a seven-item scale assessing satisfaction with one's current institution (1 = *Very dissatisfied* to 5 = *Very satisfied*) with respect to time for research, internal funding, infrastructure (e.g., space, technology, technical assistance, etc.), institution commitment to research, opportunities to develop new programs, student support, and collaboration (i.e., colleague co-authorship, social support, etc.). Four social-environmental factors reported by faculty as important to their success were measured using four-item scales from Stupnisky et al. (2015, 2019a; 1 = *Strongly disagree* to 5 = *Strongly agree*): personal balance (e.g., "I have been able to balance my work and home/personal life"), professional balance ("I have been able to balance my teaching, research, and service work"), clear expectations ("I have come to understand what the expectations are for me at work"), and collegiality ("There is someone in my department who I can ask for advice and guidance").[2]

Rationale for Analysis

Analyses began with descriptive statistics and reliability analyses on all study variables to examine if the data sufficiently met statistical assumptions, such as normality and scale internal consistency. The scales were then averaged into variables, faculty mean levels of motivation were generally noted, and ANOVAs were used to test faculty differences based on rank. We conducted correlations to examine bivariate relationships among all study variables.

Latent variable analyses were conducted using the R lavaan package for structural equation modeling (SEM; Rosseel, 2012). Latent variables in SEM are the operationalization of a construct (e.g., autonomous motivation) that cannot be measured directly, but can be represented by multiple indicators (i.e., scale items on a survey; Hair et al., 2013). Latent variables are advantageous as they better represent theoretical constructs and improve statistical estimation of the relationships between constructs by accounting for measurement error. First, a confirmatory factor analysis (CFA) was conducted to test the relations of the observed/measured variables to the latent/unmeasured variables (Marsh et al., 1999). This measurement model included latent variables for the three basic psychological needs, four

[2] The study data will be shared upon request to the first author. This study was not preregistered.

motivation types, and a second-order perceived success variable (first-order latent variables for activity, publication, and grants). Second, a structural model tested the predictive/regression hypotheses that faculty research basic needs would be positively associated with autonomous motivation and, in turn, positively related to self-reported success; alternatively, extrinsic and amotivation types were expected to have small or negative relationships with basic needs and success. The structural model also included covariates predicting research success, which were averaged into manifest variables to reduce model complexity. Criteria used to assess the model goodness of fit included: chi-square (χ^2), standardized root mean square error (SRMR < 0.05 indicates well-fitting model, Byrne, 2010; < 0.08, Hu & Bentler, 1999; < 0.10, Kline, 2005), the comparative fit index (CFI > 0.95 indicates a well-fitting model, < 0.90 requires respecification; Bentler, 1990; Hu & Bentler, 1999), and the root mean square error of approximation (RMSEA < 0.08 indicates an acceptable-fitting model, Browne & Cudeck, 1993; < 0.10 MacCallum et al., 1996).

Quantifying the number of publications and citations achieved by faculty yields *count data*, which requires unique analytic strategies (Beaujean & Grant, 2016). Whereas typical linear regression models assume a normal distribution of the outcome variable (e.g., self-reported research success on a Likert scale), count variables are often positively skewed yielding a Poisson distribution (i.e., most values are relatively low, few are high). Applying typical linear regression methods to count data can lead to biased parameter estimates (Beaujean & Grant, 2016), and other strategies such as dichotomizing responses or nonlinear transformations (e.g., square root) to make the variable more closely approximate to normal have significant limitations. Poisson regression models assume a non-normal distribution and link predictor variables to the outcome via a natural log transformation; however, they also assume that the means and variances of variables are equal. *Negative binomial* regression models account for the overdispersion of scores (i.e., when the variance is larger than the mean) and thus were used in the current study. Limitations of negative binomial regression include not applying well to small samples, outcome variables cannot have negative numbers, and under-dispersion (i.e., when the variance is smaller than the mean); fortunately, the current study did not meet any of those conditions.

Results

Reliabilities and Mean Levels

The items all showed sufficiently normal distributions (i.e., skewness less than 2.3, Lei & Lomax, 2005; kurtosis less than 7.0, Byrne, 2010). The scales generally had good reliability based on Cronbach's alpha (adequate > 0.70, good > 0.80; Warner, 2013). External motivation was below adequate reliability but retained due to its conceptual importance, while positive introjected motivation was dropped from all further analyses due to its low reliability.

Faculty reported high mean levels of autonomy, competence, and relatedness for research, and in turn, reported relatively high levels of autonomous motivation for research compared to negative introjected, external, or amotivation. Several differences were found among faculty based on their rank (Table 3). Full professors had the highest levels of autonomy, competence, autonomous motivation, and perceived success, as well as the lowest negative introjected and external motivation. Assistant professors reported the highest relatedness. Associate professors had the poorest profile overall, including the lowest autonomy, autonomous motivation, and perceived success.

Differences were also found based on discipline. Life and Lab Science faculty (biology, chemistry, geoscience, physics, astronomy, etc.) had significantly higher autonomous motivation, publications, and citations than faculty in Social Sciences (psychology, STEM education, etc.) or Math and Engineering (includes CISE, materials research, etc.). Faculty in social science, however, reported more relatedness than faculty in math and engineering.

Finally, several mean differences were found between international versus domestic STEM faculty. International faculty, compared to domestic, reported significantly more autonomous motivation [$t(625)=2.36$, $p=0.04$, $M_{\text{int}}=4.54(0.49)$, $M_{\text{dom}}=4.42(0.56)$], less amotivation [$t(356)=-2.30$, $p=0.02$, $M_{\text{int}}=1.74(0.72)$, $M_{\text{dom}}=1.90(0.88)$], more perceived success [$t(630)=3.54$, $p<0.001$, $M_{\text{int}}=3.51(0.71)$, $M_{\text{dom}}=3.27(0.75)$], and a great number of publications [$t(436)=2.66$, $p<0.001$, $M_{\text{int}}=9.15(8.25)$, $M_{\text{dom}}=7.19(6.55)$].

Correlations

Correlations revealed strong support for SDT among faculty (Table 4). For instance, moderately large positive correlations were found among autonomy, competence, relatedness, and autonomous motivation. These constructs had significant positive correlations with perceived success, the largest coming from competence. Alternatively, the basic needs and research success had negative correlations with faculty introjected, external, and amotivation for research. The remaining variables had small yet significant correlations with research success, the largest being professional balance, which justified them being included as covariates in subsequent analyses.

Latent Variable Analyses Predicting Self-reported Success

Following an initial analysis of the measurement model, modification indexes suggested inclusion of correlated error terms among two external motivation and two amotivation variables, as well as among the perceived success items with matching reference points (e.g., self-standard for research activity, publication, and grants). The final CFA showed adequate goodness-of-fit to the data, $\chi^2(657)=1510.23$, RMSEA $=0.047$, CFI $=0.939$, SRMR $=0.056$, as well as strong item-to-factor loadings (>0.70) supporting the quality of the measures.

The structural model (Fig. 2) had adequate goodness-of-fit to the data, $\chi^2(925)=2313.85$, RMSEA $=0.052$, CFI $=0.901$, SRMR $=0.102$. Autonomy and competence had the largest positive predictive relationship with autonomous motivation, which together explained 43% of the variance. Surprisingly, relatedness did not relate significantly to autonomous or other motivation subtypes. Competence was negatively related to introjected motivation, whereas autonomy was negatively related to external motivation. Autonomy also had a strong negative relationship with amotivation (the largest coefficient in the model), with amotivation having 43% of its variance explained by the predictor variables. Autonomous motivation was positively related to self-reported research success, however the other motivation subtypes did not predict self-rated success. Of the success

Table 3 Rank differences on motivation and research success

Measure	Rank					Discipline				
	Assist	Assoc	Full	*F*	*Eta-sq*	Math and engineering	Life and lab science	Social science	*F*	*Eta-sq*
Basic needs										
Autonomy	4.13(.63)	4.04(.71)^{a}	4.21(.63)^{b}	3.07**	.01	4.12(.64)	4.12(.66)	4.13(.66)	0.01	.00
Competence	4.17(.59)^{a}	4.23(.58)	4.34(.53)^{b}	5.27**	.02	4.22(.60)	4.26(.55)	4.22(.60)	0.33	.00
Relatedness	3.99(.64)^{a}	3.81(.76)^{b}	3.98(.73)	3.59*	.01	3.83(.78)^{a}	3.90(.73)	4.06(.64)^{b}	3.78*	.01
Motivation										
Autonomous	4.44(.51)	4.04(.50)^{a}	4.55(.57)^{b}	4.20*	.01	4.34(.62)^{a}	4.56(.51)^{b}	4.42(.50)^{a}	9.14***	.03
N. Introjected	3.59(.99)^{a}	3.39(1.00)	3.13(1.03)^{b}	4.31*	.01	3.45(1.11)	3.33(1.02)	3.51(.97)	1.93	.01
External	3.60(.83)^{a}	3.63(.79)^{a}	3.41(.76)^{b}	4.44*	.02	3.57(.84)	3.48(.81)	3.57(.86)	0.82	.00
Amotivation	1.78(.79)	1.83(.81)	1.80(.81)	0.12	.00	1.97(.84)	1.84(.84)	1.78(.84)	2.17	.01
Success										
Perceived	3.45(.70)	3.18(.72)^{a}	3.49(.75)^{b}	8.71***	.03	3.36(.81)	3.32(.74)	3.35(.70)	0.13	.00
Publications	7.06(6.63)	7.63(7.02)	8.65(7.66)	1.84	.01	7.79(7.71)	8.83(7.42)^{a}	5.63(5.70)^{b}	7.82***	.04
Citations	20.02(27.62)^{a}	26.54(39.26)	34.37(47.55)^{b}	4.59*	.02	27.76(44.27)	33.35(43.52)^{a}	15.36(23.02)^{b}	7.65***	.04

Significant ANOVAs on faculty rank were followed up with Tukey tests, for which group differences are indicated by different subscripted letters. Disciplinary groupings were Math & Engineering included engineering, mathematics sciences, CISE, and materials research ($n = 147$); Life & Lab Science included life science (e.g., biology), chemistry, geoscience, physics, and astronomy ($n = 286$); Social Science included social sciences generally, psychology, and STEM education learning research ($n = 171$)

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 4 Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Autonomy	–														
2. Competence	.60**	–													
3. Relatedness	.56**	.40**	–												
4. Autonomous motivation	.54**	.47**	.40**	–											
5. Introjected motivation	− .03	− .11**	− .02	.05	–										
6. External motivation	− .14**	− .06	− .08*	− .15**	.18**	–									
7. Amotivation	− .52**	− .38**	− .37**	− .61**	.08*	.22**	–								
8. Perceived success	.32**	.39**	.27**	.31**	− .09*	− .02	− .22**	–							
9. Career age	.04	.12**	.02	.08*	− .13**	− .10*	.04	− .02	–						
10. Research % on contract	.08*	.12**	.04	.17**	− .02	.12**	− .06	.12**	− .07	–					
11. Institutional support	.28**	.12**	.35**	.12**	− .10**	.08	− .10*	.18**	− .08*	.10*	–				
12. Personal balance	.28**	.18**	.27**	.13**	− .13**	.00	− .11*	.18**	.05	.08*	.38**	–			
13. Professional balance	.40**	.39**	.31**	.21**	− .21**	.04	− .20**	.35**	.05	.16**	.44**	.67**	–		
14. Clear expectations	.30**	.25**	.41**	.18**	.00	.07	− .17**	.23**	− .08*	.07	.36**	.32**	.46**	–	
15. Collegiality	.32**	.09*	.52**	.18**	− .02	.03	− .25**	.09*	− .21**	− .02	.50**	.26**	.27**	.51**	–

$^{*}p \leq .05$, $^{**}p \leq .01$

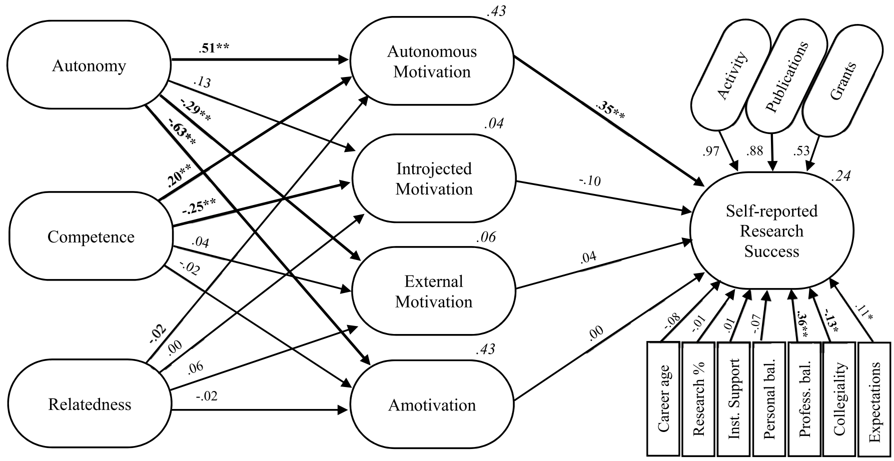


Fig. 2 Structural Model of Faculty Motivation and Research Success. Bold paths and coefficients are significant at * $p < .05$, ** $p < .01$

covariates, only professional balance and clear expectations positively related to research success, whereas collegiality was negatively related.

Negative Binomial Regressions Predicting Bibliometric Success

Table 5 contains correlations, typical simultaneous multiple linear regressions, and hierarchical negative binomial regressions (mean-centered predictors) predicting faculty publications and citation counts. Correlations and typical regressions revealed relationships among the study variables with research success outcomes, such as research percentage on contract, basic psychological needs, and autonomous motivation. However, the coefficients were weak, likely due to the outcome variable being positively skewed count data.

Step 1 of the hierarchical negative binomial regression included all success covariates and basic psychological needs, with results showing research percent (contract) to be a positive predictor of publications and citations, and competence and relatedness to predict publications. In Step 2a, autonomous motivation was added as a predictor and was the strongest positive predictor in the model. In Step 2b, autonomous motivation was removed and amotivation added, which was one of the biggest negative predictors in the models. In Step 2c, all motivation types were entered simultaneously, and although the predictive significance of autonomous and amotivation decreased, they remained among the most important predictors of publications and citations. We also observed evidence of mediation as autonomy was positively correlated with publications and citations but became nonsignificant or significantly negative with the inclusion of autonomous motivation in the models. This suggests autonomy predicts change in faculty publications via autonomous motivation.

Further interpreting the results of the negative binomial requires exponentiating the values as the log link makes the regression values difficult to interpret. The exponentiated intercept represents the predicted number of publications and citations with all other

Table 5 Regressions predicting bibliometric research outcomes

	Publications						Citations					
	r	Typical regression	Hierarchical negative binomial				r	Typical regression	Hierarchical negative binomial			
			Step 1	Step 2a	Step 2b	Step 2c			Step 1	Step 2a	Step 2b	Step 2c
Intercept (sq. root)		7.45**	1.98 (7.24)	1.96 (7.07)	1.96 (7.10)	1.95 (7.05)		26.33**	3.21 (24.85)	3.18 (24.13)	3.19 (24.38)	3.18 (24.16)
Success covariates												
Career age	.01	− .03	.00 (1.00)	.00 (0.99)	.00 (1.00)	.00 (1.00)	.03	.01	.00 (1.00)	.00 (1.00)	.00 (1.00)	.00 (1.00)
Research %	.20**	.19**	.01** (1.01)	.01** (1.01)	.01** (1.01)	.01** (1.01)	.14**	.14**	.01** (1.01)	.01** (1.01)	.01** (1.01)	.01** (1.01)
Inst. support	.05	− .08	− .07 (0.94)	− .08 (0.92)	− .08 (0.92)	− .08 (0.92)	.00	− .03	− .05 (0.96)	− .04 (0.96)	− .09 (0.92)	− .06 (0.94)
Personal balance	.11*	.07	.10 (1.11)	.11 (1.11)	.12 (1.12)	.12 (1.12)	− .01	− .05	− .09 (0.91)	− .11 (0.90)	− .08 (0.93)	− .10 (0.90)
Pro. balance	.15**	.12	.07 (1.08)	.12 (1.13)	.09 (1.09)	.12 (1.12)	.06	.06	.00 (1.00)	.07 (1.07)	.03 (1.03)	.07 (1.08)
Clear expectations	.09	.02	.02 (1.02)	.04 (1.04)	.06 (1.05)	.05 (1.05)	.05	.06	.19 (1.21)	.23 (1.26)	.26 (1.29)	.26 (1.29)
Collegiality	.02	− .06	− .05 (0.96)	− .07 (0.93)	− .08 (0.92)	− .10 (0.91)	− .03	− .12†	− .16 (0.85)	− .20 (0.82)	− .19† (0.82)	− .21† (0.81)
Basic Needs												
Autonomy	.10*	− .17*	− .13 (0.88)	− .22* (0.80)	− .21* (0.81)	− .24* (0.78)	.10*	− .02	.12 (1.13)	− .03 (0.97)	.06 (1.06)	− .04 (0.96)
Competence	.18**	.05	.20* (1.23)	.12 (1.13)	.14 (1.15)	.09 (1.10)	.12**	− .01	.11 (1.11)	− .01 (0.99)	.02 (1.02)	− .04 (0.95)
Relatedness	.16**	.15*	.18* (1.20)	.17* (1.19)	.17* (1.18)	.18* (1.19)	.12**	.12	.15 (1.17)	.16 (1.17)	.14 (1.15)	.15 (1.17)
Motivation												
Autonomous	.18**	.10		.28* (1.33)		.20† (1.23)	.15**	.10		.43* (1.54)		.37† (1.44)
Introjected	− .04	.00				− .02 (0.98)	.01	.04				.00 (1.00)
External	.00	.01				.02 (1.02)	− .02	− .01				− .01 (0.99)
Amotivation	− .15**	− .09			− .18** (0.83)	− .14† (0.87)	− .10*	− .03			− .19† (0.82)	− .12 (0.89)
AIC		2614.0	2464.6	2379.7	2421.9	2360.1		3960.6	3363.2	3262.3	3313.7	3236.5
BIC		2685.6	2518.3	2438.0	2480.1	2431.7		4032.3	3416.9	3321.0	3371.9	3308.2

† $p < .10$, * $p < .05$, ** $p < .01$

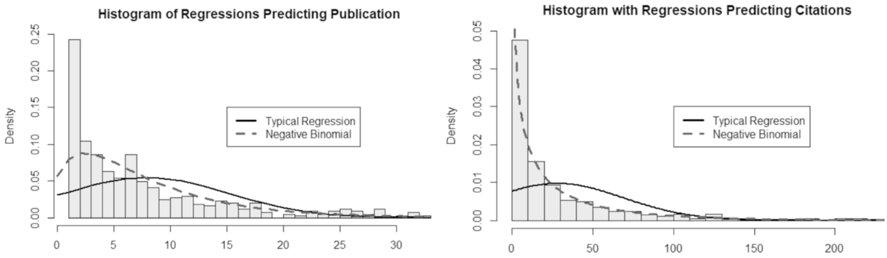
In Negative binomial column, top coefficients are standardized regression weights and lower coefficients in parentheses are exponentiated coefficients for interpretation variables at the average. In the current sample with all predictors in STEP 2c, STEM faculty were predicted to achieve 7.05 publications and 24.16 citations. The regression coefficients, after exponentiated to place them on their original scale, can be interpreted as the rate the outcome count will go up with each one unit increase in the predictor. The coefficient can also be interpreted as a percentage change in the expected counts (for formula see Beaujean & Grant, 2016). For example, Step 2c indicates that with every SD increase in autonomous motivation (0.55, about half a 1–5 Likert scale response option), faculty achieve an 11.63% increase in publications (1.23 times the 7.05 intercept = 8.67 total publications) and a 22.57% increase in citations (1.44 times the 24.16 intercept = 34.79 total citations) over three years.

Figure 3 shows histograms of observed faculty publications and citations with predicted values from typical and negative binomial regressions. Typical regression for publication and citation data underestimates the number for faculty in the lower range and overestimates for faculty at higher ranges. Negative binomial predictions were noticeably closer to the actual numbers of publications and citations in the sample. Goodness of fit was assessed with the Akaike information criterion (AIC) and Schwartz's Bayesian information criterion (BIC) for which smaller values typically indicate a better model. As the AIC and BIC values of the negative binomial regressions were smaller than the typical regressions, this suggests they fit the data better.

Discussion

With the current study, the authors sought to better understand faculty research success by examining the role of motivation. The principal finding was that autonomous motivation for research, which represents engagement based on enjoyment and valuing scholarly activity, was the strongest predictor of faculty research success. This finding supports past studies showing motivation to be an important predictor of faculty research outcomes (Hardre et al., 2011; Walker & Fenton, 2013; Stupnisky et al., 2017). This study further improved upon the past studies on faculty motivation by (1) examining motivation beyond intrinsic (i.e., autonomous) motivation to consider the roles of introjected and external motivation, as well as amotivation; (2) using a large, multi-institution sample of faculty members across a variety of STEM disciplines; (3) utilizing multi-item scales and latent variables in structural equation models to improve the reliability and validity of findings; (4) measuring research success with self-report and bibliometrics; and (5) controlling for other common, non-motivation variables related to faculty success.

Upon seeing the main finding some readers may remark, "It is self-evident that people who enjoy research are going to be more success, so why is this finding important?" We would argue that the current findings highlight that autonomous motivation is undervalued within the academic community and higher education generally, relative to other factors. For instance, common knowledge and some existing research might indicate that faculty are more successful researchers if they have been in the career for longer, have a larger research percentage on their contract, feel more supported by their institution, have good work-home balance, good collegial relations, and/or clear expectations for outputs. However, our findings show none of those factors to be as important as autonomous motivation. Although some may also believe that researchers can be motivated by financial incentives and awards (external motivation),



Publications	Actual	Predicted with Typical	Predicted with NB	Citations	Actual	Predicted with Typical	Predicted with NB
1	66	2.99	30.91	5	16	1.64	11.95
3	46	8.35	33.62	10	9	2.55	7.77
5	28	31.95	29.21	25	4	15.71	3.65
10	11	40.87	15.72	50	3	2.03	1.58
15	10	1.44	7.60	75	1	0.00	0.81
25	4	0.01	1.73	100	1	0.00	0.45

Fig. 3 Histograms with tables showing actual and predicted values for regression models

or pressuring them into productivity through guilt or stringent tenure and promotion requirements (negative introjected motivation), those factors also were not found to be as important as autonomous motivation in the current study. The only factor that was comparatively as impactful as autonomous motivation for faculty research success in our latent variable analyses was having good professional balance (i.e., between teaching, research, and service). In the negative binomial regression analyses, the only other significant motivation type was amotivation, suggesting faculty who have low engagement in research are at significant risk of lower research productivity. As the bibliometric data from this study reveals many faculty are not publishing at high rates and their work is not heavily cited, it is important to acknowledge autonomous motivation as a primary determinant of faculty scholarly productivity.

To improve research productivity, it thus follows that post-secondary institutions should aim to bolster faculty autonomous motivation. The current study found faculty with more autonomy and competence also reported more autonomous motivation, which is consistent with self-determination theory (Ryan & Deci, 2017) and past research on faculty motivation (Stupnisky et al., 2019a). Although research on faculty motivation interventions is limited, these findings suggest that autonomy could be fostered by encouraging faculty to choose research questions and scholarly pursuits that are most aligned with their values, whereas some faculty may feel pressured to research topics that are "fundable". There is also growing support for the benefits of an autonomy-supportive work environment that provides meaningful rationales, acknowledges negative feelings, uses noncontrolling language, offers meaningful choices, and nurtures internal motivational resources (Reeve & Cheon, 2021; Su & Reeve, 2011). The results also suggest that autonomy is important for reducing external motivation and amotivation, which can have deleterious effects on research productivity. Competence can be promoted by universities offering ample opportunities for professional development, such as attending workshops, conferences, and facilitating collaborations. Faculty reporting greater feelings of competence also felt less negative introjected motivation for conducting research (i.e., guilt when not engaging in research) thus potentially further contributing to the psychological well-being of research-intensive faculty (e.g., by promoting work-life balance).

Limitations and Future Directions

Although the current study addressed several limitations of past research on faculty motivation, there are several future directions available for better understanding how motivation impacts research productivity in faculty. For instance, as the current study was cross-sectional in nature, although the bibliometric data covered three years, studying the effects of motivation on faculty research longitudinally will allow more confidence in motivational variables as predictors of research productivity and greater understanding of their long-term stability and effects. Such data would also allow analyses and insights into possible reciprocal relationships between motivation and productivity (i.e., autonomous motivation predicts productivity, and in turn productivity predicts autonomous motivation). Additional motivation theoretical perspectives may provide insights into faculty research success (e.g., Goal Theory, Control-Value Theory of Emotions, etc.), as would consideration of complementary constructs (e.g., stress and coping; Salimzadeh et al., 2017).

Also, here we studied all STEM faculty holistically, however important subgroups, such as based on discipline and those representing underrepresented minorities (O'Meara et al., 2020), may have different experiences in how motivation affects their research. We did not include discipline and more demographic variables in the main analyses because the empirical measurement of these variables is debatable. For example, the number of faculty in the NSF defined STEM disciplines varied dramatically (e.g., Life Sciences 178, Materials Research 5) with some being too small to analyze as their own group; thus, for the mean difference analyses the disciplines were combined into three groups based on similarity, although other configurations could be done. Similarly, citizenship in the current survey was measured with the item, "Do you consider yourself an 'international' faculty member? For example, born and raised outside of USA."; however, among faculty who would answer "Yes" there could be vast differences between a new faculty member who just arrived from Canada (geographically close to the US) and a senior faculty member from far overseas (e.g., Africa or Asia) who has been working in the US for decades. Thus, we chose to include in the analyses only variables for which the measurement was clear.

Similarly, future research investigating relations between the study variables at other institution types, such as R1, Doctoral/Professional Universities, and Master's College and Universities, would be beneficial to ascertain the extent to which the present findings generalize to institutions at which faculty conduct research at differing rates. Finally, with a literature that has now established the importance of motivation for research success, interventions designed to specifically foster autonomous motivation to improve faculty research productivity should be developed and tested.

The current study results should be informative to higher education institutions, particularly those striving to increase scholarly productivity, as to specific strengths and deficits in faculty motivation for research that contribute to measurable gains in research activity. Ultimately, our findings should help to provide guidance to universities, government, and industries on how to best support research faculty in STEM domains to produce innovative basic and applied scientific knowledge, to tackle key social and economic challenges with their research, and to train the next generation of flexible, knowledgeable, and diverse researchers.

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Declarations

Conflict of interest We have no known conflict of interest to disclose. This study was not preregistered. The study data will be shared upon request to the first author.

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