



Entrepreneurial orientation, technological propensity and academic research productivity



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ABSTRACT

To what extent are academics entrepreneurial, and to what extent does an entrepreneurial orientation contribute to higher research productivity in higher education? According to some schools of thought, academic research is conducted within ‘paradigms’ or circumscribed areas of study, with the implication that certain research might not be inherently innovative. This research sought to investigate the extent to which individuals with higher self-reported levels of entrepreneurial orientation (EO), as well as the propensity to apply novel technological methods (such as crowdfunding and crowdsourced R&D) in their research, have higher levels of research productivity. Applying a comprehensive purposive sampling process, a large South African university was sampled. A total of 292 usable responses were obtained, and these were analysed using ordinary least squares. In order to test the robustness of results, two further tests were applied, namely bootstrapping and negative binomial regression analysis. Findings suggest that individuals with higher endowments of entrepreneurial orientation may be more research productive. Interestingly, innovativeness is not found to be significantly related to academic research productivity. It is concluded that further synthesis between educational and entrepreneurship theory might offer useful insights for the improvement of societally important research productivity. It is also concluded, however, that novel technological methods such as crowdfunding may be underutilised in the academic context. Given the resource constraints faced by those in higher education, particularly in the developing-country context of this study, this underutilisation may point to important opportunities in the sector.

1. Introduction

What is not clear in the entrepreneurship literature is the extent to which academic staff are entrepreneurial, and the extent to which an individual with a higher entrepreneurial orientation (EO) is more research productive, given the performance advantages typically associated with entrepreneurial orientation (Lumpkin and Dess, 1996). Similarly, given potential advantages associated with the application of technology to the research process itself, more entrepreneurial academics may also be more likely to pursue novel technological opportunities in their research. We use the term ‘technological propensity’ to refer to the extent to which individuals seek to use new technologies to enhance their productivity in working contexts. In resource-constrained developing country contexts, such as South Africa, this knowledge may be particularly important, in that newly developing technologies may offer researchers opportunities to be more research productive, at a lower cost. This research therefore adds to other work in the Southern African higher education context (Samuel and Chipunza, 2013; Farrington et al., 2012;

Khaola, 2014), and specifically work on entrepreneurial orientation in this context (Fatoki, 2012; Matchaba-Hove et al., 2015), to explore the relationships between academic research productivity and both entrepreneurial orientation and technological propensity.

In the context of this research, academic research productivity is taken to function in a similar manner to the commercial production of goods and services, in that both are subject to certain trends (Brynjolfs-son and McAfee, 2012). Like commercial production, the process of academic knowledge creation is dependent on the availability of raw materials. Indeed, evidence suggests that scientific advancement occurs as the result of “standing on the shoulders of giants” (Bornmann et al., 2010, p.1), also described as “discovering truth by building on previous discoveries” (Keith et al., 2016, p.359). From this perspective, academic researchers rely primarily on their contemporaries to provide ‘raw input’ (i.e. academic knowledge) on which to produce new knowledge (Tian et al., 2009). In the context of commercial production, improvements in the production process are driven by changes in technology. For Christensen (1997, p.2), ‘technology’ can be understood as:

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...the processes by which an organization transforms labour, capital materials and information into products and services of greater value. All firms have technologies.... The concept of technology therefore extends beyond engineering and manufacturing to encompass a range of marketing, investment, and managerial processes. Innovation refers to a change in one of these technologies.

Applied in the context of academic research production, this definition of technology would extend to the research methodologies and paradigms employed by academics to drive the academic 'production process'. Thus, innovation in this context refers to changes in research methodologies and paradigms. The relatively recent emergence of distributed knowledge systems, such as the Internet, have had profound effects on knowledge creation, availability and dissemination (Von Krogh, 2012; Von Krogh, Nonaka & Rechsteiner, 2012), which arguably suggest the potential for certain productivity-improving innovations in the research process itself.

Innovation theory predicts that the diffusion of innovation is often dependent on individual-level adoption (Centola, 2010). Rogers (2010) differentiates between individual innovation adoption categories, emphasising the importance of innovators and early adopters in the diffusion of the innovation process. Innovators and early adopters are characterised as risk takers, opinion leaders and social leaders (Iyengar, van den Bulte and Valente, 2011). In the context of this research, innovators and early adopters would be expected to have high levels of technological propensity and to therefore produce more research output than those with low levels of technological propensity.

Despite the seemingly positive consequences of changes in the research process, concerns regarding 'knowledge overload' have been raised (Bock et al., 2010). The oversaturation of knowledge inputs as a direct consequence of distributed knowledge systems might be considered a technological disruption (Fullwood et al., 2013). Radical technological disruptions are often met with resistance (Christensen, 1997). As per Christensen's (1997) definition, new technology is required to either (i) mitigate the potential threats, or (ii) exploit the potential opportunities, of a given disruptive innovation. Therefore, technological change may offer important opportunities for the improvement of academic research productivity, in terms of both quantity and innovative quality. Those academics that are not resistant to technological (or methodological) change may be more likely to produce more innovative research output.

Definitional understandings of entrepreneurship can be useful in understanding how and why some individuals identify opportunities, evaluate them as viable, and then decide to exploit them, as well as how entrepreneurs use these opportunities to develop new products and services (Shane and Venkataraman, 2000; Davidsson, 2015). It is argued therefore that academic researchers that are entrepreneurial by nature may be able to effectively identify technological or methodological opportunities and therefore may produce new knowledge more efficiently.

For Lumpkin and Dess (1996), individual-level 'entrepreneurial orientation' (EO) is a behavioural construct that can capture the dimensions of entrepreneurial behaviour typically exhibited by entrepreneurs. This construct is comprised of behavioural dimensions associated with risk-taking, competitive aggressiveness, autonomy, pro-activeness and innovativeness (Lumpkin and Dess, 1996). Innovativeness, as a component of EO, is of particular interest in the case of academic researchers, since innovation is commonly considered a prerequisite in generating valuable knowledge outputs (West and Bogers, 2014; Heinenon, 2015). In a context in which radically enhanced technological capabilities exist, this study seeks to test the extent to which academics with higher levels of EO are more effective at pursuing research opportunities, and have higher levels of total research output, measured as scientific journal article production. Furthermore, academic researchers that produce more research output may be more likely to produce more innovative research output than their counterparts.

This study therefore tests theory that predicts that individuals with

higher levels of EO have higher levels of total research output. The extent to which an individual is open to the use of certain technological innovations as levers of research productivity, or an individual's technological propensity, and its relation to research output, is also investigated. The extent to which technological propensity mediates the contribution of EO to research output is also tested. This research is considered particularly important as academic research is tasked with the production of societally important innovations and knowledge creation. Having briefly provided an introduction to the study, theory is now considered which relates the variables under study. Next, the methodology of the study is discussed. After this, the findings of the study are reported and discussed. Finally, conclusions and recommendations for further research are considered.

2. Theory

To understand relationships at the nexus of entrepreneurial behaviour, the use of certain technological opportunities, and potential improvements in the efficiency of academic research, it is necessary to take recourse to theory relating to the effectiveness of research knowledge creation itself.

According to Callaghan (2018), the problem of 'knowledge aggregation' is concerned with the impediments to triggering knowledge interactions to generate innovative outputs. Theory relating to the knowledge aggregation problem essentially draws from three theoretical concepts. *Firstly*, in private organisational contexts, knowledge is typically proprietary (firm specific) in terms of intellectual property regimes (Smith, 2010), and in general is unevenly distributed (Hayek, 1945). *Secondly*, knowledge is inherently decentralised (Hayek, 1945; Von Hippel, 1976). *Thirdly*, knowledge is 'sticky' (Von Hippel, 1976); it resides within individuals as tacit knowledge rather than within organisations and is very difficult and costly to move from where it originated (Nonaka, 1994). These constraints form a threshold to knowledge creation and transfer, and thus to innovation (Smith, 2010). It is argued here that framing knowledge creation, and especially academic, or scientific, knowledge creation, in terms of constraints to knowledge aggregation is critically important, as knowledge aggregation theory provides a unifying rationale by acting as a conceptual heuristic to stress differences in the way constraints work to hold back knowledge creation. This unifying rationale is important, because it makes explicit the constraints to knowledge creation, drawing on seminal theoretical frameworks that transcend disciplinary perspectives. This rationale is also important because it suggests that it might only be through the application of technologies to the research process itself that we ultimately overcome these constraints. This study therefore makes an important contribution to this literature by explicitly testing the extent to which researchers (knowledge creators) who have a higher propensity to use novel technologies are indeed more research productive. Further, it makes a contribution to the entrepreneurial literature by explicitly relating EO theory to research output, in that innovativeness is a key component of an individual's EO.

The investigation of entrepreneurial behaviours may therefore provide a clearer indication as to the extent to which knowledge aggregation might be overcome. In the context of firms, entrepreneurial behaviour can be described as that behaviour in organisations which "engages in product market innovation, undertakes somewhat risky ventures, and is first to come up with 'proactive' innovations, beating competitors to the punch" (Miller, 1983, p.771). For Lumpkin and Dess (1996), the dimensions of EO, including innovativeness, proactiveness, autonomy, risk-taking and competitive aggressiveness, are all behavioural orientations that can exist at the individual or firm level. In the context of academic research, certain orientations of individual-level entrepreneurial orientation may contribute to research output as a quantity, the innovative value of a given level of research output, or both. Each of these dimensions is now briefly discussed, in relation to academic research productivity.

For Lumpkin and Dess (1996, p.142), innovativeness reflects a behavioural tendency, either by firms or individuals, “to engage in and support new ideas, novelty, experimentation, and creative processes that may result in new products, services, or technological processes”. In the context of academic research, innovativeness may therefore be expected to contribute to the value of a given level of research output and may also therefore contribute indirectly to research output quantity. Another dimension of EO is proactiveness, related to initiative and first-mover advantages, or to “taking initiative by anticipating and pursuing new opportunities” (Lumpkin and Dess, 1996, p.146). Lumpkin and Dess (1996, p.146) argue that proactiveness may be “crucial to an entrepreneurial orientation because it suggests a forward-looking perspective that is accompanied by innovative” and entrepreneurial activity. Proactiveness, however, might contribute to performance at an optimal level, which is contingent on context (Lumpkin et al., 2010). In the context of academic research, proactiveness may therefore be expected to be positively associated with research productivity.

Autonomy, or “independent spirit” refers to independent action in terms of “bringing forth an idea or a vision and carrying it through to completion”, including the concept of free and independent action and decisions taken (Lumpkin and Dess, 1996, p.140). Entrepreneurs are associated with a degree of freedom in combining and organising resources (Goodale et al., 2011). “A tendency toward independent and autonomous action” is a key component of an entrepreneurial orientation, since intentionality must be exercised (Lumpkin and Dess, 1996, p.140). Autonomy may therefore also contribute to the innovative value of academic research output, given that autonomous individuals may be more likely to pursue novel methodologies in their research. For Lumpkin et al. (2009, p.56), risk-taking involves “taking bold actions by venturing into the unknown, borrowing heavily and/or committing significant resources to venture in uncertain environments”. Like autonomy, risk-taking may therefore also be expected to be positively associated with the inherent innovativeness of academic research output.

Competitive aggressiveness, for Lumpkin and Dess (1996, p.148), “refers to a firm’s propensity to directly and intensely challenge its competitors to achieve entry or improve position,” or to outperform industry rivals in the marketplace. This is characterised by responsiveness in terms of confrontation or reactive action. The association between competitive aggressiveness and academic research productivity is also expected to be positive in this context.

These dimensions considered above make up the EO construct. Research productivity, or research output, might be considered an indication of the extent to which an academic researcher has succeeded in producing knowledge outputs (Levin and Stephan, 1991; Van Aken, 2005; Kyvik, 2013). What is not clear in the academic context, however, is knowledge of the specific configurational structure of the contributions of the five dimensions of EO to academic performance, as the performance impact of EO is contingent upon contextual characteristics which vary across contexts (Lumpkin and Dess, 1996). If the academic publication context is not inherently innovative, as suggested by Kuhn (1970) and Lakatos (1970), then research productivity would not necessarily be expected to be related to innovativeness, as a key dimension of EO. On the other hand, if research productivity were inherently innovative, it would be expected to be associated with innovativeness, and more broadly also to the dimensions of EO. Given this body of literature, the following hypothesis is derived.

H1. Entrepreneurial orientation is significantly and positively associated with research productivity.

The extent to which an individual is open to the use of novel or emergent technologies or has what we term here a high ‘technological propensity’, is also considered key to the reduction of constraints to knowledge aggregation in academic research.

Callaghan (2014) suggests that innovation in the research process itself occurs iteratively and that successive ‘generations’ of the research process can reflect technological change. Conventional research

processes might therefore be categorised as falling within a ‘first generation’ research paradigm, or one that is severely limited by the combined constraints of the knowledge aggregation problem and by profit-bound innovation.

However, the emergence of distributed knowledge systems has, to some extent, democratised access to knowledge (Peters, 2010; Chesbrough et al., 2014). New methods of data aggregation and analysis, such as open innovation (Chesbrough, 2003), crowdsourcing (Howe, 2006) and open source production (Brabham, 2008) have effectively ‘opened’ the innovation process by providing unfettered access to large volumes of tacit knowledge. These new methodologies may therefore be considered disruptive innovations in the research process itself, and may therefore represent important new opportunities, which if seized may offer significant improvements in the quantity and quality of academic research output. Callaghan (2014) uses the term ‘second generation’ innovation to refer to the use of these new methodologies in the research process. In the context of this research, technological propensity therefore refers to *the extent to which academic researchers engage with, and adopt, these new ‘second generation’ technologies and methodologies to enhance the quality and quantity of their research output.* Using these ‘second generation’ tools and techniques might allow researchers to overcome certain knowledge aggregation constraints, through the use of big data collection or big data analysis; methods associated with open innovation. These second generation techniques relate to the application of novel technologies to the research process itself, and we suggest that entrepreneurial individuals and those with a higher propensity to apply technology to their research, should be more research productive.

Open innovation or “the use of purposive inflows and outflows of knowledge to accelerate innovation” (Chesbrough, 2006, p.2) has become increasingly enabled by new technological developments. Building on the philosophy of open innovation, probabilistic innovation theory (PIT) purports that free and open knowledge interactions can in some ways surmount constraints to knowledge aggregation (Callaghan, 2015). With these constraints addressed, knowledge inputs can flow more freely in multi-directional configurations, rather than in the dyadic structures associated with proprietary knowledge. In other words, the application of ‘second generation’ modes of productivity are probabilistic in nature; an exponential increase in knowledge availability means a potentially exponential increase in knowledge interactions. An increase in knowledge interactions means a greater potential for producing new knowledge. Ultimately, a greater potential for producing new knowledge culminates in a higher probability of producing innovative knowledge outputs. In short, the adoption and application of open probabilistic or distributed knowledge systems in the research process may increase research productivity.

Crowdsourcing is perhaps one of the most promising developments in probabilistic innovation. Defined as a distributed problem-solving and production model (Brabham, 2013), crowdsourcing essentially “represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call” (Howe, 2006: 1). Callaghan (2014) refers to crowdsourced research and development (R&D) as a methodology, or a set of methods used to generate knowledge or to source large data in ways that address the problem of knowledge aggregation. Indeed, examples of the use of crowdsourced R&D are widespread. Proteomics, or the study of large-scale proteins has become increasingly important in the identification and development of new drugs for the treatment of disease (Barsnes and Martens, 2013). Because proteomics is an exceedingly complex field and requires substantial knowledge inputs from a diverse range of expertise, distributed knowledge networks (i.e. crowdsourcing) has been used to significant effect to analyse mass data generated from proteomics research (Barsnes and Martens, 2013). Several online platforms, such as BioMart, have been established as intermediaries for this process. Further examples include the use of crowdsourcing networks for HIV-AIDS and cancer research (Torr-Brown, 2013). Some forms of medical research have also been

known to make use of a process known as gamification, or the use of game thinking and game mechanics in non-game contexts to find innovative solutions to problems (Huotari and Hamari, 2012), which is then outsourced to the crowd. A University of Washington experiment called *FoldIt* asked users to try 'solve the puzzle' of folding various protein structures (relating to AIDS research) using video-game tools and mechanics. In contrast to scientific researchers that had been working on similar problems for extended periods of time, certain solutions sourced from the crowd (players) were reached in just three weeks (Torr-Brown, 2013). Crowdfunding is a form of crowdsourcing which involves the solicitation of "small amounts from many donors" (Averett, 2013, p.908), usually over the Internet. The use of crowdfunding to finance medical research has become increasingly common (Moran, 2017). Renwick et al. (2016) suggest that crowdfunding may indeed offer a viable approach to supporting some forms of medical research, but has been inadequately explored, thus far.

These examples are drawn from an increasing body of literature that suggests different ways in which technology can be applied to the research process itself. More specifically, by harnessing the probabilistic capabilities of large numbers of people functioning collectively and in real time, some of the constraints to knowledge aggregation and innovation in academic research may potentially be mitigated.

The study of entrepreneurial orientation may provide an indication as to the likelihood of an individual's adoption of these new modes of productivity. More entrepreneurial individuals are expected to be more likely to adopt different tools and techniques that might help them increase their research productivity. Academic research has however often been strongly associated with tradition (Bechtel and Richardson, 2010) and is not typically open to sudden and drastic change. Given the cautious nature of scientific research, new research paradigms or methodologies are often rejected, sometimes needlessly so (Campanario, 2009). Indeed, academic research may be unable to adapt in the face of radical change (Alvesson and Sandberg, 2013).

For these reasons, the assumption that academic research is effective at solving serious societal problems cannot necessarily be made in all instances. Instead of producing breakthrough knowledge or breakthrough innovations, academia may be better suited to contributing small incremental advances to existing knowledge (Bastow et al., 2014). That is not to say that radical innovative academic research does not exist; rather that it typically occurs infrequently. If PIT principles, for example, do anticipate the impact of novel emergent technologies on the productivity of the research process, then the technological propensity of an individual, or the extent to which an individual is open to the use of novel technologies in their research may be an important enabler of improved research productivity, and also an important mediator of the contribution of individual entrepreneurial behaviour to research productivity.

In summary, it is suggested here that individuals with higher levels of technological propensity (defined as the extent to which individuals seek to use certain novel and unconventional technologies or methodologies to enhance their research performance) will have an advantage in research production due to the productivity-enhancing capabilities of these technologies. The productivity-enhancing potential of such novel technologies has been well documented, particularly in fields such as medical research (see Callaghan, 2015).

On account of this literature, the following hypotheses are offered.

H2. Technological propensity and research productivity are significantly and positively associated.

H3. Technological propensity mediates the relationship between entrepreneurial orientation and research productivity.

In a global knowledge creation environment enabled by important knowledge creation opportunities offered by distributed knowledge systems, together with an unprecedented availability of information and knowledge inputs (Lakhani et al., 2013), the literature suggests that such opportunities might not necessarily be related to research productivity. If

academic research fails to provide innovative research outputs (Campanario, 2009) commensurate with this growth in knowledge then knowledge creation may be constrained. A lack of societally important innovations, or slow responses to urgent societal needs, is a serious ethical issue (Fenton et al., 2015), and can maintain inequality in access to the benefits of research (Callaghan, 2019). This research therefore seeks to make a contribution to the entrepreneurial education literature through investigating the extent to which research productivity is responsive to individual EO and technological propensity. Having provided an overview of theory and literature which provided the basis for the derivation of hypotheses, the research methods applied in this study are now discussed.

3. Design

This study applied an empirical, quantitative research design (Creswell et al., 2003). The investigation was conducted within the post-positivist paradigm in that it pursued objectivity, while acknowledging the possible effects of biases (Creswell et al., 2003). It is premised on objective ontological and epistemological assumptions (Burrell and Morgan, 1979).

3.1. Data collection and analysis

The data collection process sought to sample the entire population of a large South African university, using a comprehensive purposive approach. Of a population size of about 1300 full time academic staff, 292 usable responses were obtained, with a response rate of about 23%, or a little less than a quarter of the staff. According to a sample size calculation the sample size was sufficient to test relationships at a $p < .001$ level of significance (Krommenhoek and Galpin, 2014). IBM SPSS and Stata software programmes were used to analyse the data. Regression and mediation techniques were conducted to test the hypothesised relationships between variables, based on precedent (Field, 2012).

3.2. Scales/measures

The 13-page questionnaire was comprised of four separate sections and was used to quantitatively measure the variables in the theoretical model. An adaptation of an Entrepreneurial Orientation scale (Lumpkin et al., 2009), using 5-point Likert scale items, was used to measure the five elements of EO, namely innovativeness, risk-taking propensity, autonomy, proactiveness, and competitive aggressiveness. Although a similar structure was used, this scale was adapted to suit the context of academic research.

Table 1 provides descriptions of the tested variables. The technological propensity scale was developed theoretically, with care taken to ensure construct validity and alignment with underlying theory. This scale used a 5-point Likert scale to measure the extent to which individual researchers were open to the use of certain novel methods in the practice of their research. A list of 8 different new crowdsourced R&D methodologies were listed and respondents were asked to indicate the extent to which each methodology might be useful in their own research. Concise descriptions of each of these categories was provided in the questionnaire. Each item was selected based on examples of their usefulness and success in the literature and included the following: i) crowdfunding, ii) inducement prize contests, iii) crowd-fixing, iv) crowd-searching, v) user-generated content, vi) implicit crowdsourcing, vii) crowd voting and viii) gamification.

This research extends previous research into a new context and the processes were carefully considered to maintain the integrity of the research. Questions included in the instruments were phrased in a neutral fashion to avoid social desirability bias. Content, construct, face and criterion validity (Campbell and Fiske, 1959; Bryman, 2004) were ensured throughout the sampling and instrument design stages. A pilot test was also conducted to further ensure reliability and validity.

Table 1
Definitions of tested variables.

Variable	
ARP	Academic research productivity, measured as journal article publications
Gender (male versus female)	Gender, measured as a binary variable (1 versus 0)
English	English as a home language as a binary variable (1 versus 0)
Years as a researcher	Measure of years an individual has been working as a researcher
Preference for quantitative methods	A binary preference for quantitative versus qualitative methods (1 versus 0)
Dependent children	Number of dependent children an individual has
Risk taking propensity	Likert-type scale measure of an individual's preference for risk
Competitive aggressiveness	Likert-type scale measure of an individual's competitiveness
Innovativeness	Likert-type scale measure of an individual's innovativeness
Proactiveness	Likert-type scale measure of an individual's preference for initiating, or starting, new activities
Autonomy	Likert-type scale measure of an individual's preference for individual and autonomous action
Total entrepreneurial orientation	A summative measure of the five subordinate entrepreneurial orientation measures

Following Podsakoff et al. (2012), response bias was controlled through questionnaire structure. Care was taken to use precise, simple language in item descriptions and to avoid the use of leading questions.

The last sections of the instrument included 14 questions designed to capture respondent's biographical information, and a final exploratory open-ended question designed to capture further insight that could aid a post-hoc interpretation of the results. A pilot study was conducted on the first 10% of the sample collected (Field, 2012). The pilot study revealed that the Cronbach's alpha values were stable, and no major changes were required (Field, 2012). The final alpha values were .889 for technological propensity and .774 for EO, supporting the reliability of these items.

Measures of research productivity were taken as a summative number Department of Higher Education and Training accredited journal article publications (the Department publishes a list of 'approved' publications, yearly, which also include IBSS and ISI indexed publications).

Scale items of different lengths were taken to be acceptable, as the coefficient on each tested independent variable in an ordinary least squares regression analysis summarises the relationship between the independent and dependent variable, in each case (Gujarati and Porter, 2009).

3.3. Qualitative analysis

One additional qualitative question was included in the questionnaire to draw out further insights. This question asked respondents to indicate which of the crowd-based processes might be most suitable or useful to their own research and to briefly explain why and how they would make use of the chosen process. Although brief, data recorded from answers to this question was considered helpful in contextualising the results of the primary (quantitative) analysis. Indeed, for Miles and Huberman (1994, p.1):

... [qualitative data are] a source of well-grounded, rich descriptions and explanations of processes in identifiable local contexts... [which] can offer a perspective on chronological flow, and insight into the consequences of events, which can yield fruitful explanations... good qualitative data are more likely to lead to serendipitous findings and to new integrations; they help researchers to get beyond initial conceptions and to generate or revise conceptual frameworks.

For Guba (1981, p.79), qualitative research is trustworthy if it meets the criteria of i) truth value (internal validity), ii) applicability (external

validity/generalisability), iii) consistency (reliability) and neutrality (objectivity). In this study, truth validity was ensured through the strength of the linkages between the qualitative and quantitative data. In other words, the close association between the technological propensity scale and the qualitative question. Both applicability and consistency were ensured by selecting respondents from a diverse range of fields of study, across the university population. Although Weber (1949) argues that all social science research is inherently biased, an attempt to attain objectivity was made by i) the addition of the qualitative question itself and ii) by phrasing the question in a neutral fashion. The results of this study are now discussed.

3.4. Ethical considerations

The research was conducted in accordance with national and international ethical guidelines. Anonymity and right of refusal to participate were unconditionally respected. Approval was obtained from the University's Ethics Committee prior to the research. Potential dangers (related to physical, psychological or disclosure) were reduced by ensuring that all information was kept anonymous, and relationships in the data were only reported at the aggregated level. Participation was voluntary and a consent form was given to subjects to sign. A cover sheet was also given to subjects, which informed them that participation was voluntary and that they were welcome to withdraw from the study at any time.

3.5. Specifications

The following specification was estimated in order to test the hypotheses. These specifications take the form of formulas that make explicit which variables are included in the statistical testing. The tests of mediation used the same specifications, in reduced form. The estimation process for the mediation testing is reported in depth in the appropriate section.

$$ARP_i = a_i + \beta_1 Gender_i + \beta_2 English_i + \beta_3 Experience_i + \beta_4 Quantitative_i + \beta_5 Children_i + \beta_6 RTP_i + \beta_7 INN_i + \beta_8 PRO_i + \beta_9 CA_i + \beta_{10} AUT_i + \beta_{11} TI_i + u_i \tag{1}$$

In this model, Gender is a measure of male versus female, as a binary variable (with male equal to one and female equal to zero), English a measure of whether an individual's home language is English or not. Experience is the number of years an individual has as a researcher. Quantitative is a measure of an individual's preference for quantitative methods, and Children the number of dependent children an academic has. RTP, INN, PRO, CA and AUT refer to measures of risk taking propensity, innovativeness, proactiveness, competitive aggressiveness, and autonomy, respectively. The dependent variable is ARP, or academic research productivity. A further specification was tested using the summative entrepreneurial orientation (EO) value:

$$ARP_i = a_i + \beta_1 Gender_i + \beta_2 English_i + \beta_3 Experience_i + \beta_4 Quantitative_i + \beta_5 Children_i + \beta_6 EO_i + \beta_{11} TI_i + u_i \tag{2}$$

Specifications were tested for OLS assumptions. Studentised residuals were estimated, and outliers removed if these values were greater than two or less than minus two. Seven outliers were removed for the first model. According to the Breusch-Pagan/Cook-Weisberg heteroscedasticity test (Chi-square = 400.19; p < .0001), the model was not homoscedastic. This was confirmed using Cameron and Trivedi's estimation (Chi-square = 106.89; p < .0074). The model was estimated again, using heteroscedasticity-corrected standard errors. The mean variance inflation factor for the model was 1.29, with the highest value within the model being 1.92, for the proactivity variable, suggesting

reasonable levels of multicollinearity. In order to obtain confidence intervals for the significance of the results that were relatively more robust to other outliers, the model was also run in bootstrapped form (with 5000 iterations).

For the second model (Eq. 2), 26 outliers were identified and removed. Both the Breusch-Pagan/Cook-Weisberg heteroscedasticity test (Chi-square = 115.81; $p < .0001$) and Cameron and Trivedi's estimation (Chi-square = 125.72; $p < .0074$) were significant, indicating the presence of heteroscedasticity in the model. To address this, heteroscedasticity-adjusted standard errors were applied. The mean VIF for the model was 1.08, and the highest value within the model was 1.15, for the years of experience variable.

Two further tests were applied, in that they provided additional information about the tested relationships. Bootstrapping was used to obtain a non-parametric check on the significance of the relationships. A further test was also used to estimate coefficients that are robust to the use of count data. The reason for this additional test is that research productivity forms a Poisson distribution, as it is count data. Poisson regression was therefore performed, but due to the presence of over-distribution (differences in mean values from variance values), it was necessary to perform negative binomial regression, instead. Table 3 reports the OLS, bootstrap, and negative binomial results. As can be seen from this table, the hypothesis testing results are robust to the use of these different estimation approaches. In the negative binomial model, competitive aggressiveness is weakly significant (at within the ten percent level of significance) in its association with research output, whereas in the OLS and bootstrapped models it is not significant. An individual's preference for quantitative research methods is weakly associated with research productivity in the model that uses the summative EO measure, whereas in the OLS and bootstrap models this is significant at within the five percent level. These are the only differences in the results between the three models.

4. Results & discussion

Table 2 reports the descriptive statistics for the sample. In this table, continuous variables are reported as means but proportions are reported for each of the dummy variables. The distribution across the 5 university Faculties was considered to be relatively balanced. Diversity in sample nationality, language, age and years of experience was taken to be reasonably supportive of the representativeness of the sample. The mean age of the sample was 42.5 years. Sciences Faculty staff made up about 33% of the sample, Health Sciences 24%, Humanities 24%, Engineering and the Built Environment 6%, and Commerce Law and Management 14%. The dependent variable is academic research productivity, measured by number of published journal articles (ARP in Table 1).

Hypothesis 1. Entrepreneurial orientation is significantly and positively associated with research output.

Table 2
Descriptive statistics.

Variable	Mean/Proportion	Standard Deviation
ARP	25.82	55.19
Gender (male versus female)*	0.5	0.501
English*	0.707	0.456
Years as a researcher	12.327	10.577
Preference for quantitative methods*	0.403	0.491
Dependent children	1.133	1.294
Risk taking propensity	3.424	0.761
Competitive aggressiveness	3.278	0.939
Innovativeness	3.287	0.754
Proactiveness	3.571	0.724
Autonomy	3.343	0.623
Total entrepreneurial orientation	16.903	2.716

Note: * Proportion; ARP: Academic research productivity, the dependent variable.

The positive association between total EO and research productivity was found to support seminal predictions of a positive relationship between EO and performance (Lumpkin and Dess, 1996). The results of the test of this association are reported in Table 3. Models 1, 2, and 3 in this table report the results of testing the individual EO dimensions and Models 3, 4, and 5 report the testing of the aggregate EO measure. This is in line with previous work that has used both approaches. Each model is tested using OLS (Models 1 and 4), bootstrapping (Models 2 and 5), and negative binomial regression (Models 3 and 6). The tested relationships were found to be robust to the covariate influences (by virtue of their inclusion as covariates in the tested specification) of gender, experience, and preference for quantitative methods. In terms of the specific dimensions of EO, however, differences were found in the contribution of these to research productivity. The null hypothesis was rejected. These are discussed as follows.

It is important to discuss results under the lenses of theory, and to consider the reasons why different contexts (such as organisational versus academic) may produce different results. The theory derived from the broader literature relates primarily to what might be considered *the generic working context*. Thus, when testing such theory in the academic context, results are expected to differ from this context in certain respects. The identification of these differences is considered to be a contribution to this broader body of literature, offering useful insights into how the predictions of theory differ according to boundary conditions associated with atypical contexts.

Innovativeness was not found to be associated with higher levels of research output. Within a global context of modern technologies that have in many ways had a profound effect on academia (Grimpe and Hussinger, 2013), it seems that in this specific context, innovative behaviour might not necessarily contribute to higher research productivity. It is possible that this context is atypical of other contexts, or that entrepreneurial innovativeness associated with seizing opportunities to develop new processes (Shane and Venkataraman, 2000; Davidsson, 2015) do not transmit to research productivity increases in this context.

If there is no 'payoff' to the innovativeness behavioural dimension of EO, then this result may echo the assertions of Kuhn (1970) that academic progress might not necessarily be innovative in nature. If innovativeness is typically a prerequisite to generate superior knowledge outputs (Heinonen, 2015) then it is possible that research outputs are not responsive to innovativeness, or that research productivity is not constrained by non-innovative behavioural orientations of individual researchers or enabled by innovative behavioural orientations.

This result finds support in certain literature. Alvesson and Gabriel (2013, p.245) have critiqued the standardisation of research and publications "into formulaic patterns that constrain the imagination and creativity of scholars and restrict the social relevance of their work." Further research should therefore apply qualitative, or causal research methods in order to understand the causal influences that underlie these findings. Such causal research might either support or contest this important notion, that academic research productivity might not be associated with entrepreneurially innovative behaviour. It bears noting here that if there were reverse-causality in the relationship between innovativeness and research productivity then one might still expect a significant association. Here, there is no significant association.

With the exception of a weak association in the negative binomial model for competitive aggressiveness, neither proactiveness, competitive aggressiveness nor risk taking propensity were found to be significantly associated with research productivity. Entrepreneurial behaviours associated with proactively acting first, or being the first to proactively undertake activities is typically expected to also be related to innovativeness, as are risk taking behaviours. Thus, innovativeness, proactiveness and risk taking behaviours are not found to offer an advantage in research productivity in this context. Further research might explore other dimensions along which academic research productivity differs from that of other forms of work productivity. Competitive behaviours associated with entrepreneurial competitive

Table 3
Determinants of research output.

VARIABLES	(1)	(2)	(3)	(5)	(6)	(7)
			Negative			Negative
	OLS	Bootstrap	Binomial	OLS	Bootstrap	Binomial
	ARP	ARP	ARP	ARP	ARP	ARP
Gender	6.541*** (2.337)	6.541*** (2.356)	0.299** (0.144)	6.563*** (2.317)	6.563*** (2.339)	0.290** (0.143)
English	-0.308 (2.362)	-0.308 (2.331)	0.0482 (0.162)	0.101 (2.335)	0.101 (2.310)	0.0301 (0.168)
Years as a researcher	1.911*** (0.215)	1.911*** (0.213)	0.0770*** (0.00680)	1.920*** (0.213)	1.920*** (0.212)	0.0773*** (0.00690)
Preference for quantitative methods	7.761*** (2.597)	7.761*** (2.550)	0.305** (0.144)	6.969*** (2.592)	6.969*** (2.535)	0.279* (0.148)
Dependent children	-1.430 (1.026)	-1.430 (1.013)	0.0188 (0.0548)	-1.370 (1.026)	-1.370 (1.015)	0.0154 (0.0574)
Risk taking propensity	1.114 (1.702)	1.114 (1.688)	0.0358 (0.109)			
Innovativeness	-1.080 (2.156)	-1.080 (2.186)	0.0608 (0.109)			
Competitive aggressiveness	1.118 (1.465)	1.118 (1.482)	0.157* (0.0893)			
Autonomy	6.431*** (1.976)	6.431*** (2.007)	0.230** (0.109)			
Proactiveness	-0.569 (2.177)	-0.569 (2.222)	0.0250 (0.134)			
Technological propensity	-0.717 (1.295)	-0.717 (1.334)	0.0103 (0.0747)	-0.449 (1.286)	-0.449 (1.316)	0.0235 (0.0742)
Total entrepreneurial orientation				1.046** (0.448)	1.046** (0.449)	0.0967*** (0.0273)
Constant	-28.58*** (9.925)	-28.58*** (9.995)	-0.455 (0.560)	-24.02** (9.546)	-24.02** (9.583)	-0.409 (0.546)
Observations	292	292	292	292	292	292
R-squared	0.537	0.537		0.526	0.526	

Robust standard errors in parentheses.

***p < 0.01, **p < 0.05, *p < 0.1.

aggressiveness might be antithetical to academic life, and it is perhaps not surprising that such behaviours are not strongly related to productivity in this context. These findings support Lumpkin and Dess's (1996) theoretical predictions that the contributions of different EO dimensions to performance are context specific. Further research might extend this research to investigate other differences between this academic context and other, perhaps more entrepreneurial, contexts.

Autonomy, however, was found to be a significant predictor of research productivity. As a behavioural entrepreneurial orientation, autonomy in the form of independent action, or "bringing forth an idea or a vision and carrying it through to completion" and demonstrating free and independent action and decisions (Lumpkin and Dess, 1996, p.140) seems to be the only dimension of EO that research productivity is sensitive to, while seemingly non-responsive to innovativeness, or individual behaviours associated with new processes, techniques or new ways of doing things. There might be a pay-off in this context for autonomous opportunity seeking behaviour, but not for innovative opportunity seeking behaviour. If so, then if technological propensity, or the pursuit of new technologically enabled opportunities, is essentially considered to be strongly related to innovativeness, it would perhaps also be expected to be non-significant in its association with research productivity.

Autonomy associated with freedom in combining and organising resources (Pearce et al., 2010) is key to an entrepreneurial orientation, but a paradox exists here if autonomy is associated with higher research productivity, but innovativeness is not. This begs the question, is there no payoff to innovativeness in academic publishing, at least in terms of research productivity? If academic researchers are inherently non-innovative in the way they pursue opportunity, their inclination to make use of innovative technological propensity processes may therefore be severely impeded.

Nevertheless, the evidence found here is taken to support a positive

relationship between overall EO and research productivity, supporting its hypothesised link to performance across contexts (Lumpkin and Dess, 1996). Important implications derive from this finding. Entrepreneurial education might usefully be incorporated into tertiary teaching qualifications. Whereas the benefits of entrepreneurial behaviour are recognised across different contexts, the specific benefits of EO for the research project have to date been under-researched.

Over and above EO, individual behaviours of academic staff might specifically channel opportunity seeking behaviour toward certain more specific outcomes. Technological propensity is taken to be an important complement to EO in that it relates to a specific way in which opportunity might be pursued in academic contexts. However, to the extent that technological propensity relates to the use of technologies that are especially innovative, and beyond the mainstream, the uptake of such technologies to support the research process might be considered akin to radical innovation (Bers et al., 2009). There is a long history that suggests that many may be hesitant to accept and incorporate radical innovations into practice (Smith, 2010). Thus, knowledge of the extent to which technological propensity is related to research output in the academic context might provide useful insights into the tolerance of academics for radical innovations that relate to the research process itself.

Hypothesis 2. Technological propensity is significantly and positively associated with research output.

The tests of this hypothesis are reported in Table 2. Technological propensity is not found to be significantly associated with research productivity. The null hypothesis was not rejected. Given that technological propensity is a measure of the propensity of an individual to engage in the use of certain emergent technological processes to improve the effectiveness or efficiency of their research, these results suggest that technological propensity is not contributing to higher research productivity in this context. This finding may suggest that the academic context

is atypical of other more general working contexts in which technological propensity might drive productivity increases.

It is possible that the system of research publication is not as yet responsive to technological advances of this nature, or to their application by researchers, despite the potential of new technological developments to produce radical improvements in known performance features or a significant reduction in cost (Bers et al., 2009) in other contexts. It is possible that this context is not typical of other contexts. Further research is recommended, in order to replicate this research in other contexts. The tests for potential mediation of the relationship between EO and research productivity by technological propensity are now discussed.

Hypothesis 3. Technological propensity mediates the relationship between Entrepreneurial Orientation and research output

To test this hypothesis, mediation was conducted using Hayes (2013) PROCESS model for SPSS. Hayes' (2013) PROCESS model fits a series of regression models using the terms M (mediator), X (independent Variable) and Y (dependent variable). Technological propensity (TI) was not found to mediate the relationship between entrepreneurial orientation and research output. Hayes' (2013) PROCESS model fits a series of regression models using the terms M (mediator), X (independent Variable) and Y (dependent variable). First, the model predicts the mediator variable using the independent variable (Step 2), then the dependent variable using both the independent variable and the mediator (Steps 3 and 4); and finally, the dependent variable using the independent variable (Step 1). The following is a summary of the application of the four steps:

- 1) Path C: EO (X) predicts ARP (Y) (Total Effect Model)
 - a. $F(1, 298) = 14.693, p > 0.05, R^2 = 0.047$
 - b. $b = 22.022, t(298) = 3.833, p < 0.05$
- 2) Path A: EO (X) predicts TI (M) (Outcome: TI)
 - a. $F(1, 298) = .375, p > 0.05, R^2 = 0.0013$
 - b. $b = -.062, t(298) = -.612, p > 0.05$
 - c. This model is not significant (X does not predict M)
- 3) EO (SX) and TI (M) together, predict ARP (Y) (Outcome ARP)
 - a. Overall model: $F(2, 297) = 7.353, p < 0.05, R^2 = 0.047$
 - b. Path B: TI (M) predicting ARP (Y)
 - i. $b = -.792, t(297) = -.243, p > 0.05$
 - c. Path C': EO (X) no longer predicts ARP (Y), or is lessened, predicting ARP (Y)
 - i. [X and M predicting Y] $b = 21.972, t(297) = 3.833, p < 0.05$
- 4) Sobel Test (normal theory test) = z score test if $c - c' \neq 0$
 - a. $Z = .124, p = .900$

Because Path C' is significant, this indicates partial mediation. The Sobel Test then shows that C and C' are different when M is included in the model. With no mediator present, $ARP = 22.022$, but with the mediator present, $ARP = 21.972$, which means an increase in ARP when controlling for TI Propensity. Therefore [total effect of X on Y (22.022)] – [direct of X on Y (21.972)] = the indirect of X on Y (.049). A measure for the indirect effect of X on Y is also provided. In this case, the effect was present with a 95% confidence interval which did not include zero; that is to say the effect was significantly greater than zero at $\alpha = .05$. Thus, it can be concluded that TI Propensity does not change the relationship between EO and ARP and mediation does not occur. The null hypothesis is not rejected.

On the basis of these estimations, it can be concluded that technological propensity does not significantly provide a channel through which the relationship between EO and ARP can flow more effectively, and mediation is not supported. Although those who do exhibit characteristics of an entrepreneur, and particularly autonomy, do seem to obtain a pay-off in terms of research productivity, this effect does not seem to act through the use of novel technological applications. It is insightful to note that innovativeness does not obtain such a pay-off in

this context, in much the same way as the application of technological innovations also does not. These results support Lumpkin and Dess' (1996) broader assertion that while entrepreneurial orientation and performance are typically positively related, different EO dimensions contribute differently to performance, contingent upon context. In order to better understand how technological propensity might contribute to academic performance, a single qualitative question was included at the end of the instrument. These responses are now discussed in order to provide a more fine-grained understanding of the results.

4.1. Qualitative responses

On the basis of the additional exploratory open-ended qualitative question, further insight into respondents' views on crowdsourced R&D was obtained and to further ensure convergent and discriminant validity (Campbell and Fiske, 1959). These insights are considered particularly important, given the lack of an association between technological propensity, and indeed innovativeness, and research productivity. The open-ended nature of the question allowed for a grounded approach and required the respondent to mention different processes specifically. These short responses generally seemed to support the results of the quantitative findings. The question asked respondents to indicate which of the 8 crowdsourced R&D processes would be most applicable to their field of expertise and thereafter to provide a brief description of why and how it would, or would not, be used in their research. The mean of the frequency of mentions of each of the technological propensity processes is shown in Table 3. Thereafter, responses to the short qualitative question, in the broader context of the research are briefly discussed (see Table 4).

Crowdfunding was the process most frequently selected by respondents and seemed to generate significantly more interest than the other processes presented in Table 3. In describing the potential usefulness of crowdfunding, respondents often referred to the severely bureaucratic nature of the conventional research funding process, noting that crowdfunding may be a useful tool in combatting the restraints of resource cost in academic research. The assertions of Renwick et al. (2015), that crowdfunding may offer a viable alternative to funding certain academic research is supported by this finding. Indeed, a trend of support for the use of crowdfunding in academic research has become increasingly evident. In 2015, for example, an experiment at the Australian Deakins University successfully raised over AUS\$185,000 for 19 different research projects by crowdfunding alone (Palmer and Verhoeven, 2016). For Roberts (2017, p.17) "the time is now ripe for university management...to embrace new technology platforms as part of their strategic finance planning to take advantage of new emerging revenue models in combination with existing operations".

Items related to the broader notion of distributed knowledge aggregation, including crowdsourcing, crowd-fixing, crowd-searching and crowd-voting all received similar amounts of interest. Crowd-voting, or collective contributions to decision-making, was the most popular option amongst these. Crowd-voting was described as a dependable way of improving efficiency and quality of research outputs, especially from "from industry captains and practitioners".

Table 4
Crowdsourced R&D process frequency.

Technological Propensity Process:	Proportion
Crowdfunding	.21
Inducement Prize Contests	.07
Crowd Fixing	.10
Crowd-searching	.13
User-Generated Content	.10
Implicit Crowdsourcing	.08
Crowd-voting	.15
Gamification	.07

In general, the use of crowdsourced R&D was described as a potential way to generate new ideas, to construct databases or networks and to expedite or streamline the research process. Indeed, the seeking of a common response (“to know what everyone thinks”) and to get an ad hoc sense of popular opinion through a much bigger sample proved to be an important aspect of crowdsourcing receptiveness. Combined, interest in crowdsourcing and its sub-components (including crowd-fixing and crowd-searching) were relatively high, although respondents in different fields of study tended towards either sourcing, fixing or searching, depending on the nature of their research needs.

Some of the more common responses to the question included references to the enhancement of public interest and the potential to expose their work to potential collaborators or even to “criticism that will further improve subsequent research.” The question also elicited references to local and international academic cooperation and cross-disciplinary collaboration. More specific examples include the use of crowdsourcing to find localities of plants and insects in biological research, to sample rural populations in social research, or to classify galaxies in astronomical research. In line with the Ortega Hypothesis, or the attainment of scientific progress by building on previous discoveries (Keith et al., 2016; Bornmann et al., 2010), respondents also cited ‘collaborative learning’ as way to ‘scaffold information’, to solve structural problems and to model complex concepts using the crowd. Both user-generated content (UGC) and gamification also elicited positive responses, related to the use of social media, open source software and the combined use of inducement prize contests and gamification to yield higher sample sizes, higher levels of engagement and task motivation.

These findings suggest a certain willingness exists, to adopt more open methodologies in the research process. Indeed, for Lakhani et al. (2013, p.2), “the transfer of scientific knowledge” is a critical component of innovation; one that may become increasingly fluid in the era of distributed knowledge systems. Not all responses, however, were positive. Two quotes in particular, characterised the dichotomy of perceptions on the use of crowdsourcing in academic research.

“The world is changing, this is the new potential of problem solving.”

“I am deeply suspicious of crowds, not enough caution, too many frauds.”

Negative responses mostly related to issues of quality management and validation of input from the crowd. Concerns that providing incentive (inducement prize contests) may provide incentive for fraudulent research were also raised. Many respondents claimed that their research had no need for new research processes of any form. Others noted that the some of these tools may indeed be useful, but only in conjunction with more traditional techniques.

The results of the open-ended exploratory question offer certain useful insights into the non-significance of technological propensity item in the statistical testing. Although the potential of these new technological developments seems to be recognised by most of the respondents, there are certain concerns about the use of these methods, such as validity issues, and the extent to which these methods have developed sufficiently in their usage as to be useful in more specific research tasks. It is possible that the need for validity in scientific research in general outweighs certain advantages of innovative behaviours or processes in this context. It seems the advent of the Internet, distributed knowledge systems and subsequent ‘knowledge overload’ (Bock et al., 2010) which has necessitated a change to how information and knowledge is obtained in other contexts, may not be having a dominant effect in the academic context. Entrepreneurship itself however, is generally not associated with academic research not explicitly related to commercial applications, because of its non-profit nature (Gibson and Klocker, 2004). Research in the same context has previously found that Schwartz’s innovative values are not higher for more productive researchers (Callaghan, 2017). Further causal research is recommended, particularly qualitative research, in order to understand the causal mechanisms which underlie

these findings. Having reported and discussed the findings of the study, summary conclusions and recommendations for further research follow.

5. Conclusions

The main finding of this study is taken to be the positive relationship between total EO and research productivity (Hypothesis 1), which suggests that the benefits of EO for performance also extend to the academic context, insofar as they relate to the production of research. The significance of autonomy as a specific dimension of EO related to higher levels of research productivity also offers an important insight into which specific channel EO might work through in its contribution to research performance.

The paper offers certain unique contributions to the literature. *First*, it identifies the lack of a significant relationship between technological propensity, or innovativeness, and research productivity (Hypothesis 2). It also demonstrates that technological propensity does not mediate the relationship between EO and research productivity (Hypothesis 3). This finding gives rise to certain implications, including the fact that little evidence is found here to contest the longstanding notion that certain academic research productivity might indeed inherently be non-innovative (Kuhn, 1970), or non-responsive to innovative opportunity-seeking behaviour of academics that relates to what the literature suggests are breaking developments in technology that can improve the efficiency and effectiveness of academic research.

Second, the paper makes a theoretical contribution, with certain important implications for practice. The specific advantages for the research process associated with technological propensity relate to how technological applications can better manage the problem of knowledge aggregation (Hayek, 1945; Von Hippel, 1976; Nonaka, 1994), but research productivity might not be inherently sensitive to behaviours and methods which contribute to knowledge aggregation in other contexts. For example, failure to take up opportunities associated with crowd-funding in a resource constrained context such as South Africa might indicate a missed opportunity.

It is possible that the academic system as it stands is relatively effective at ensuring validity and rigour, but that it might take some time for the novel technological tools and techniques associated with a technological propensity to reach mainstream academic practice, at least in this context. Crowdfunding, for example, might be a useful complement to existing methods of raising funding for research, but remains under-utilised (Keith et al., 2016; Bornmann et al., 2010). Similarly, the data collection and analysis capabilities associated with crowdsourced R&D have proved important in other contexts (Torr-Brown, 2013), yet this study shows that in this context few of these tools and techniques have yet been taken up in research processes.

5.1. Limitations

Certain limitations need to be acknowledged. Refusals on the part of potential respondents, or those who declined to participate, may have skewed the representivity of the sample. It must also be acknowledged that the statistical methods employed here are not capable of testing causality. The inferences of this study are therefore limited to those associated with theory testing research. The study used theory-testing as its primary approach but did not apply causal methods of testing, such as formal experimentation. The study design sought to reduce method bias as much as possible, and the Harman test was performed to ensure that common method bias was not a primary threat to the interpretation of the results (Podsakoff et al., 2003). Given that it was not possible to apply causal methods, it must be acknowledged that reverse causality may exist in certain of the significant associations found here. Notwithstanding this limitation, the results here offer certain useful insights, in that they provide support for certain theory, and indicate where support for other theoretical predictions is lacking, in this context.

The cross-sectional nature of this study is also a limitation. However,

theory was used to specify relationships to test. In this way, evidence was used to reduce the knowledge ‘problem space’ related to the relationships under study. Further longitudinal research in this context is recommended, so as to extend this work. The multi-determined nature of social science variables is also acknowledged as a limitation associated with the approach of this study, as it is for most similar studies. Another limitation of the study was that it only assessed numbers of publications, and did not assess other metrics, such as h-indices. Further research would do well to build on these findings, using other measures of research productivity. Notwithstanding these limitations, this research arguably offers useful insights into the tested relationships in this context, providing further research with a helpful basis on which to build.

5.2. Future research directions

The findings of this research suggest certain future research directions. Further research, and particularly qualitative, or causal research, is recommended, in order to investigate the causal mechanisms that underlie these findings. On account of the overall positive relationship between EO and research performance, further synthesis between entrepreneurial and educational research streams is recommended, particularly given the pressing need for societally important research, particularly in contexts such as this one. However, further research might do well to also apply causal methods to investigate the lack of a relationship in testing found here between research productivity and the EO dimensions of entrepreneurial innovativeness, proactiveness, risk taking propensity and competitive aggressiveness. If research productivity is an important contributor to societal outcomes, the lack of knowledge as to why these aspects of EO do not contribute to productivity in this context may deny stakeholders certain opportunities to improve the productivity of societally important research.

Research might usefully build on the findings here to better understand the conditions under, and the extent to which an individual's technological propensity might not contribute to research productivity, much as in the same way as it does not for innovativeness, or certain innovativeness-related aspects of EO such as proactiveness and risk taking propensity. Although this research is not causal, it highlights a plausible conclusion, that innovative, and even technologically-innovative behaviours might not improve research productivity in this context.

Further causal research, for example using grounded theory, might therefore offer causal explanations for these findings, particularly in terms of the directional of this causality. Knowledge of the potential for reverse causality in future empirical testing would also be important. Given the societal implications of the conclusions here, further research is necessary, to test this using different methods, so as to strengthen the rigor upon which such conclusions are premised.

Declarations

Author contribution statement

A. Rubin conceived and designed the instruments, analysed and interpreted the data, and wrote the first draft of the paper. C. Callaghan provided conceptual input, performed additional statistical tests, and prepared the paper for publication.

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