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Increasing Literacy in Quantitative Methods: The Key to the Future of Canadian Psychology

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Abstract

Quantitative methods (QM) dominate empirical research in psychology. Unfortunately most researchers in psychology receive inadequate training in QM. This creates a challenge for researchers who require advanced statistical methods to appropriately analyze their data. Many of the recent concerns about research quality, replicability, and reporting practices are directly tied to the problematic use of QM. As such, improving quantitative literacy in psychology is an important step towards eliminating these concerns. The current paper will include two main sections that discuss quantitative challenges and opportunities. The first section discusses training and resources for students and present descriptive results on the number of quantitative courses required and available to graduate students in Canadian psychology departments. In the second section, we discuss ways of improving quantitative literacy for faculty, researchers, and clinicians. This includes a strong focus on the importance of collaboration. The paper concludes with practical recommendations for improving quantitative skills and literacy for students and researchers in Canada.

Keywords: quantitative methods, statistics, challenges, opportunities, training, collaboration, graduate courses, psychology in Canada

Increasing Literacy in Quantitative Methods:

The Key to the Future of Canadian Psychology

Quantitative methods (QM) play a central role in psychological research and training. Researchers suggest that courses focusing on statistics and methodology are amongst the most important for fostering critical thinking and reasoning (Lehman & Nisbett, 1990; VanDerStoep & Shaughnessy, 1997). The challenge is that these courses are often students' least favourite (e.g., Conners, McCown, & Roskos-Ewoldsen, 1998; Schutz, Drogosz, White, & Distefano 1998). One of the reasons for this lack of enthusiasm for QM courses is that many students experience 'statistics anxiety' (e.g., Dillon, 1982; Ziedner, 1991). In their review, Onwuegbuzie and Wilson (2003) found that approximately two-thirds to three-quarters of graduate students experience statistics anxiety. This anxiety often invokes avoidance (e.g., of taking classes, trying newer statistical methods; Onwuegbuzie, 2004), which presents an obvious predicament since knowledge and training in QM is crucial for most researchers in the discipline. With concerns about reporting practices, research quality, and replicability, improving literacy in QM becomes a worthwhile endeavour to reduce some of these discipline-wide issues.

In this paper, QM refers to any tests, procedures or approaches used to analyze numerical data from psychological studies. This could include statistical tests for relationships (e.g., *t*-tests, correlation coefficients), statistical modeling (factor analysis, structural equation modeling), psychometric analyses (e.g., Cronbach's α), etc. It would not include purely qualitative analyses (e.g., grounded theory) since they do not focus on statistics, nor would it include methods exclusive to research design (e.g., experimental design, survey strategies). We acknowledge, however, that a research design heavily informs the statistical methods adopted.

The question of interest is how to reconcile the importance of learning and improvement in QM, with the fact that most researchers may not actively seek (and may instead avoid) new training opportunities that would improve their understanding and use of modern QM? The goal of the current paper is to discuss some of the quantitative challenges that psychology students and researchers face, and present practical opportunities and recommendations for improving statistical literacy. Specifically, the paper will be divided into two major sections: 1) QM challenges and opportunities for students; and 2) QM challenges and opportunities for researchers, clinicians, and faculty. Before this discussion can take place, it is worthwhile to discuss the context for why improving the way psychology approaches QM is important.

Innovations in Quantitative Methods

There have been numerous statistical and technological advances in the field of psychology (e.g., new methods for dealing with missing data, robust statistics), yet psychological researchers do not always take advantage of these methods (Sharpe, 2013). Mills, Abdulla, and Cribbie (2010) found that citations for original articles in quantitative journals are minimal, which may suggest that researchers are not aware of these methods at all. Counsell and Harlow (2016) found that of the recently published empirical articles in Canadian psychology journals that used QM, the majority of the studies overwhelmingly used and reported the same univariate procedures that have been used for decades (i.e., traditional *t*-tests, ANOVAs, correlations). In many instances researchers can evaluate their hypotheses within larger models (e.g., Counsell & Harlow, 2016; Rodgers, 2010), use an equivalence test when the goal is to demonstrate a lack of relationship (e.g., Cribbie, Gruman, & Arpin-Cribbie, 2004; Maxwell, Lau, & Howard, 2015), or employ a robust alternative when faced with assumption violation (e.g., Wilcox, 2012). This is not to say that novel or advanced methods are always necessary. In fact, they are sometimes adopted by researchers who think that running procedures such as *t*-tests or ANOVAs are not advanced enough. We advocate for using the statistical method most appropriate for addressing one's research design and hypotheses (Allan & Cribbie, 2013).

With advances in technology, it is easy to collect large amounts of data using computers, cell phones, and recording technology. While these advances present incredible advantages for data collection, they often create a disparity between data richness and analytical capabilities. Researchers in psychology may collect complex information about their participants, but lack the skills and tools to effectively analyze it. A further challenge occurs when researchers rely on statistical software programs that do not allow for timely inclusion of statistical advances. Here, even if the researcher identifies and understands the most appropriate data analytic strategy, it may not be available in popular software packages like SPSS or EXCEL. This problem is common as many graduate level programs do not teach more advanced software programs (e.g., R, SAS) that are apt to include more modern methods.

Quantitative Training for Students in Psychology

Little exposure to advanced statistical methods may be, in part, due to lack of coverage in graduate level statistics courses. Graduate courses are where many researchers have their last formal training in statistical methods. Research suggests that course curricula in psychology programs across North America are nowhere close to keeping up with methodological advances (Aiken, West, & Millsap, 2008; Aiken, West, Sechrest, & Reno, 1990). In these two studies, Aiken and colleagues examined the material covered in QM courses in psychology, and found that the number of courses required and their subsequent coverage of statistical topics was insufficient. They also found little to no improvement in the programs between the almost 20 years separating the two surveys. In both cases, students were, on average, only required to take

1.2 years worth of QM classes, and there was little to no change in the course material across the two surveys. Despite the many statistical and methodological advances in QM, students continue to learn about the same (often outdated or inefficient) methods. Golinski and Cribbie (2009) replicated this finding that Canadian graduate level statistics courses in psychology are not teaching the advanced statistical procedures that modern day data demands.

As an aside, it is common for psychology students to learn new QM tools through online materials and resources. Youtube videos, websites, and blogs provide informal methods of learning that can significantly improve students' skills and stimulate interest in QM topics. While we encourage learning from a variety of platforms, these approaches should not be students' only options due to lack of coverage from their department. Less statistical coverage in graduate courses is discouraging because one of the best ways to progress in a field is through improvement in graduate student training. Better quantitative training for graduate students will indubitably improve the quality of future research because graduate experiences are likely to set the stage for how researchers think about and use QM in psychology.

Quantitative Methods Courses across Canadian Psychology Departments

Whereas Aiken et al.'s (1990; 2008) results were informative, we wanted to focus on the graduate level statistical training in Canadian psychology departments. Specifically, we sought to examine the QM course requirements and the number of QM courses available. Although, Canadian universities have a limited number of specialized QM programs in psychology departments, it is important to pinpoint distinctions in statistical training for students in a QM program compared to students who are not in a QM program (e.g., clinical, cognitive, social). We acknowledge that there may be key distinctions between different areas of psychology (e.g., clinical or experimental); however students across non-QM areas often have the same degree requirements for QM courses, and may be more similar to one another in attitudes towards statistics in comparison to students who specialize in QM.

To examine the QM courses available to graduate students, we surveyed psychology departments across Canada. The list of Canadian universities was obtained from the Canadian Psychological Association's (CPA) website (CPA, 2016). Departments that included graduate programs where the highest psychology degree was at the Masters level were not included. Universities with multiple campuses (e.g., University of Toronto) were not counted several times; instead we used program information from the main campus or main department of psychology website to avoid higher weighting in the frequency table. In total, we identified 35 psychology departments in Canada that offered PhD degrees.

We totalled the number of QM courses required by the end of a doctoral degree, as well as the number of QM courses available through the department. Degree requirement and course offering information was typically posted on the university's department of psychology website. If this information was not available, or it was unclear, we contacted faculty from the department to confirm the totals. All but two universities confirmed the QM course information. We define a ‘course’ as a single term (semester) class. In other words, a class that runs for the full academic year would be coded as two courses. A distinction was drawn between QM courses and ‘research methods’ courses. These latter types of courses were not counted unless they included a significant focus on statistical skills or topics. Research design/methods courses that cover material such as survey creation were not counted in the totals; however, if a course included information about experimental design with a focus on factorial analysis of variance, general linear models, power analysis, or taught statistical software, it was counted as a QM course.

INSERT TABLE 1 ABOUT HERE

Descriptive information about QM course requirements and offerings across Canadian psychology departments is presented in Table 1. This information is presented separately for departments with and without a QM area. The difference in course offerings between departments with a QM area and those without is large (on average, 8.50 versus 3.48), however the courses required by non-QM students in departments with a QM program are not substantially higher than the program requirements of departments without (2.67 versus 2.07). We found a wide range on the number of required courses for students in a QM program. At McGill University, for example, QM students are required to take two QM courses because the majority of their program is project or thesis based. By contrast, York University requires their QM students to take nine courses. This variability speaks to the fact that some universities require more breadth in QM, whereas others emphasize specialized research projects.

A few other important considerations are worth discussing. Directed readings or specialized seminar courses without a course code designated for a QM topic were not included in the course offerings total. It is not possible to include total numbers of these types of courses for each department as they are dependent on a number of highly variable factors such as faculty willingness and teaching load, student interest, etc. This may have underestimated the total number of QM courses available to students; however, some programs may list courses as available to students despite them having never been taught, or when they have been offered a limited number of times in the past. In these cases, the number of QM classes available to students may be slightly exaggerated. Despite these limitations, we believe that the course totals are reflective of the current available QM resources for students across Canadian psychology departments. It is also worth noting that there were few differences in course requirements by substantive area, but whether they are taken at the Masters or doctoral level tended to differ. For example, experimental students typically are required to take QM courses earlier in their graduate training than clinical students.

Graduate Training in Quantitative Methods Programs

Although some methods used in psychology were derived directly from mathematics or statistics, many were derived within social sciences or altered to fit the needs of psychological researchers. Examples of statistical methods derived out of a necessity for analyzing social science data include multilevel modeling (European Social Survey Education Net, 2013), item response theory (Bock, 1997), factor analysis (Mulaik, 1987), and structural equation modeling (SEM) (Matsueda & Press, 2012). The quantitative needs of psychological researchers are extensive and the instruction for these methods must emphasize their application for psychology, with an appropriate balance between theory and application. Psychology departments that offer a specialization in QM attempt to meet these instructional needs. The mission of these programs is to train psychologists who research, teach, and consult with psychological researchers on quantitative issues. Below we discuss some challenges and opportunities of these programs.

Few psychology departments in Canada offer a specialization in QM. For example, CPA (CPA, 2016) lists the University of British Columbia (UBC), Simon Fraser University, the University of Manitoba, the University of Western Ontario, York University, and McGill University as having specialized QM programs. One challenge for these programs is that the number of primarily-affiliated faculty members is small. York University, with four primary QM faculty members, is the largest; however the mode across all universities with QM programs is only two faculty members. Consider that the teaching responsibilities of these faculty members include both undergraduate and graduate level QM courses. The psychology department at UBC, for example, has two primary QM faculty members but 12 graduate-level QM courses available. It is evidently a challenge, even with assistance from other faculty members, to offer all of these courses regularly. Other programs may offer fewer courses in order to be able to teach these courses more frequently, but then the challenge becomes providing students with the breadth of topics. Although much of the training of QM students comes through interactions with their supervisor and other faculty members (e.g., research, practica), this training is often highly specialized; courses help to fill the gaps in the students learning and develop the more generalized knowledge required of a quantitative methodologist.

Another challenge for students and faculty in QM programs is that the students may not have obtained a strong quantitative background before entering the program. Many undergraduate psychology programs offer only one or two statistics courses, which is insufficient preparation for a masters or doctoral level program in QM. Students who recognize their interests in QM early in their undergraduate training may take courses in mathematics, statistics, or computer programming; however, most are unaware of QM as an area of specialization until late in their undergraduate degree. A final challenge for QM programs, which is highly related to the challenge above, is attracting competent students. Few students have heard of a specialization in QM, and for those who have, many have little to no interest in statistics or pursuing a career in QM. Therefore, QM programs must compete for the same few students. As the title of Clay's (2005) piece in the APA monitor concludes, there are "too few in quantitative psychology".

Despite these challenges, the opportunities for students graduating from QM programs are plentiful. In addition to their QM research, these students are able to publish substantive area psychology research using cutting-edge methods. This could be first hand research or research in settings where they serve as the statistical analyst on the project. These publications, together with the student's QM work in their field of specialization, contribute to the development of a strong research profile. Although extremely dated, between 1991 and 1996 the ratio of the number of advertised positions in QM psychology to the number of earned doctorates was 2.4 (American Psychological Association [APA], 2016). This should not come as a surprise given the challenge discussed above regarding finding students for QM graduate programs, and reinforces the plentiful job opportunities for QM students. [As highlighted by anonymous reviewers, more current research related to psychology training and the availability of post-graduate positions is needed.] QM students may have more opportunities for positions within universities and their skillset also lends well to non-academic positions. As data become easier to collect, test publishing companies, government, and industry organizations search for individuals with the strong data analytic skills gained by QM students.

Graduate Training in non-QM Psychology Programs

Current research highlights the importance of encouraging greater understanding and thinking about the concepts and themes essential to quantitative learning and statistical literacy (Garfield & delMas, 2010; Harlow, 2014). Perhaps the largest challenge in teaching QM courses is that not all psychology graduate students are immediately interested in this area and many have a great deal of anxiety about QM (Harlow, Burkholder & Morrow, 2002). It is useful to consider a number of approaches that can be used to provide opportunities for greater QM learning, particularly for those who may not initially think that they can benefit from, have the necessary skills for, or even enjoy gaining experience in QM. For example, QM teaching could involve greater active learning, mentoring, and e-learning, as well as encouraging learning outside the classroom at workshops and conferences, and reaching a broader range of students including those from underrepresented backgrounds (see Harlow, 2013). Another important component regarding learning statistics is not only learning about the available methods but also becoming aware of the bigger issues pertaining to QM. For example, learning SEM or hierarchical linear modeling is valuable, but also understanding how these methods fit into discussions surrounding issues like hypothesis testing, multiplicity control, Bayesian methodology, or ‘big data’ issues, is also valuable.

A common theme that emerges in research is the importance of encouraging attitudes, not just emphasizing quantitative skills. Attitudes such as high confidence and low anxiety are related to statistics performance as well as previous quantitative skills when students were engaged in a learning enhanced QM course that involved activities such as peer mentoring, consulting corners, research projects, and sharing and clarifying what they understood and did not understand about the statistical material (e.g., Harlow, Burkholder, & Morrow, 2002; Ramirez, Schau, & Emmioğlu, 2012). A novel approach was taken by Bringle, Reeb, Brown, and Ruiz (2016) who emphasized encouraging students to use and understand statistics and research methods while engaged in a service learning project. Their approach is consistent with other research that highlights the effectiveness of a passion-driven problem-based approach to learning statistics through hands-on projects with actual datasets (Dierker, Kaparakis, Rose, Selya, & Beveridge, 2012). Dierker and colleagues also found that this active learning approach, where each student worked on and presented their own research poster that showcased statistical analyses, was evaluated as rewarding and challenging, and left students wanting to use or develop their skills in another statistics or research course. Although many students may not initially take interest in QM due to their perceived challenges and anxiety, research demonstrates that carefully developed courses that involve a great deal of teacher and peer support tend to increase students' interest and satisfaction, and indirectly encourage them to take additional QM courses (Poelmans & Wessa, 2015). While research in this area has focused less on graduate students, we argue that findings from undergraduate samples apply similarly for graduate students.

Undergraduate Training in QM

Thus far, we have been discussing the importance of graduate-level QM training. Most often this is where faculty and departments devote most of their resources and focus on training and opportunities. This is understandable because graduate students (who are typically invested more in psychological research) are more likely to be the future generation of researchers. However, every graduate student begins their training as an undergraduate, and has made decisions about their graduate career based on their experiences in undergraduate courses and thesis projects. Exposure to a wide variety of topics and opportunities to work in research labs will have a large impact on their impression of the discipline and help them identify an area that suits them best. While most undergraduates in psychology are required to take elementary statistics classes, few students are aware that QM is an area of research. QM, instead, is taught as a course requirement, not as an area of psychology. Furthermore, it is unlikely that the professor or course director will be a QM researcher. The paucity of information about QM as an area means that otherwise interested students are less likely to pursue graduate school in QM. While it can be a real challenge to engage undergraduates in topics related to QM, there are many teaching opportunities for individuals passionate about QM to demonstrate their success in the area and the utility of methodological advances. The availability of quality instructors, courses offered, and experiences in labs creates important QM opportunities for undergraduates.

Ongoing QM Training for Faculty, Applied Researchers, and Psychologists

Thus far the paper has focused on training students, the future generations of researchers in psychology. Whereas these individuals receive more options for statistical innovation, change, and training, it remains important to provide ongoing training for professors, clinicians, and applied researchers in psychology. For the rest of this section we will use the word researcher to mean individuals who conduct psychological research in any capacity whether it is in industry, government, a clinic/hospital, or at a university.

Statistical tools learned in graduate QM courses may not remain the most relevant or best choices decades later. Instead, researchers may need new methods and skills to analyze data that were previously unavailable during graduate training. A particular challenge for researchers trying to advance their QM skills is the many constraints on their time, such as their own research, clinical practice, and teaching. Learning new skills presents a challenge, but many individuals find new QM skills to be especially difficult as higher level models and methods may require significant time and effort to master. For many, reading a textbook or journal articles may not be enough to understand and apply a new statistical procedure. An added challenge is that learning a new quantitative tool requires ongoing learning and practice as methodological advancements continue to progress. Researchers may not have the time or resources for formal training in new data analytic strategies, so the question is what should researchers do when they have data that cannot be analyzed using the methods that they already know?

Collaboration

Given the vast number of areas in psychology, it is easy for research fields to become compartmentalized and exclusive. This means that individuals within an area are likely to have similar skills and limitations. They will also be more likely to have similar perspectives on methodology and the research process. Collaborating with researchers outside of one’s own area is an excellent way to combine individual skills to strengthen research projects. While this idea applies generally, we focus on collaboration with a QM researcher. Collaboration with a methods expert may take two different forms, hiring a statistical consultant, or collaborating at some point of the research process with a QM researcher. We further explain this distinction below.

Statistical consultants. Statistical consultants are typically individuals for hire who are expected to have a range of statistical skills to help with various research problems. In some settings there may be multiple consultants with different specializations, but this is not always the case. Thompson and Edelstein (2004) note that the goal of statistical consulting is not to teach statistics, but rather to provide the client with the practical skills, tools, or knowledge to conduct their research. Thus, consultants are ‘teaching’ about recommended approaches for analyzing data, however, the level of teaching is much less rigorous than what is experienced in a class. For example, many consulting sessions are handled in just one or two short sessions; not nearly enough time to properly educate the client in the theory and application of the methods being discussed. Furthermore, statistical consultants are not always actively involved in the research or writing as a coauthor. They may be statisticians or mathematicians who had little experience in the applied research process before becoming a consultant. Statistical consultants are typically less interested in the area of research, and instead focus on ensuring that their client understands their data and analyses, and is able to interpret their results.

QM researchers in psychology. QM researchers are distinguished from consultants because they also perform research in the field of QM. Many QM researchers also have a substantive area of research in psychology, making them attractive as potential collaborators. QM researchers have their own areas of expertise, so they may not have as wide a range of skills as full time statistical consultants, but their specialized QM skills can be extremely valuable when matched with appropriate projects, and they typically have more knowledge of research in psychology and manuscript writing than a statistical consultant.

Given these differences, the choice of a statistical consultant or QM researcher depends on the researcher's goals for collaboration. If a researcher has funds available, wants someone to assist with data analysis, but does not want to offer authorship, a statistical consultant may be more appropriate. The relationship will often be confined to the specific research project for which one hires the consultant. On the other hand, if the researcher wants a collaborator to contribute to the methodology and statistics as well as the project as a whole (and potentially future work), a QM researcher is likely more appropriate. Relationships with consultants tend to be one sided; consultant is providing a service. Relationships with QM researchers are often two-sided; they contribute the methodological know-how and the substantive researchers contribute knowledge of the field and authorship. Collaborating with statistical consultants or QM researchers is becoming easier than ever; with advancements in online face-to-face technology, such as Skype, one can hire consultants in other geographical regions when none are available locally.

Additional QM Resources

While we argue that collaboration is the most fruitful way to conduct research, we acknowledge that it may not always be plausible. There are a number of other quantitative resources that can help researchers in psychology with improving their QM skills.

Journal articles. While QM journals like *Psychological Methods, British Journal of Mathematical and Statistical Psychology*, and *Structural Equation Modeling* publish articles on advanced methods that may not be very accessible to non-QM researchers, some also offer tutorials and review articles. These papers discuss software tools, topics, or statistical methods helpful to both QM and non-QM readers. For example, Canadian researcher Dennis Jackson is the lead author on a highly cited and understandable *Psychological Methods* review paper on reporting practices for confirmatory factor analysis. In another clearly written, high-impact paper, Hu and Bentler (1999) discuss cut-off values for SEM fit indices. In a broader forum, the Canadian journal, *The Quantitative Methods for Psychology* has the sole aim of providing accessible articles on statistical topics. Furthermore, substantive journals sometimes include methodological papers on topics relevant for the types of analyses conducted in that area. One example is Nasiakos, Cribbie, and Arpin-Cribbie (2010), who published a paper on using equivalence testing in psychotherapy research. Setting a goal like reading one QM paper relevant to the types of data or analyses in one's research area each week is a small but manageable way to keep current with advances in QM. Additionally, researchers can subscribe to receive email alerts or set up an RSS feed for journals that may include methodological articles of interest. These are just simple strategies to help stimulate researchers to explore some of the modern QM recommendations and methods that may be applicable to their research.

Textbooks. Whereas many researchers have accumulated some general textbooks on statistical methods, it might be more advantageous to invest in some texts on more focused analyses that relate directly to the specific designs that a researcher frequently adopts. For example, if one often uses longitudinal designs in their research, it might be more effective to have texts devoted to these type of data (e.g., *Applied Longitudinal Data Analysis*, Singer & Willett, 2013). A number of books are devoted to teaching specific topics using software as well. Consider Barbara Byrne, a Canadian methodologist, who has written several top-selling and very easy to understand books on using SEM with programs such as AMOS (Byrne, 2010) or Mplus (Byrne, 2012). Rex Kline is another Canadian methodologist who has published a highly cited, accessible, and impactful text on SEM (Kline, 2015). Another excellent text resource is the emerging trend of handbooks. These compilations include chapters on various issues pertaining to a specific topic. For example, Rick Hoyle's (2012) *Handbook of Structural Equation Modeling* contains chapters by experts in the field on a variety of basic and advanced topics such as theory, model specification, power analysis, multilevel SEM, and Bayesian SEM.

Conferences and workshops. CPA started a quantitative methods section in 2013 that offers full-day and shorter workshops, posters and symposia with a mix of sessions on novel statistical advances as well as teaching statistics sessions. Attending the QM sessions also provides opportunities to network with QM researchers, facilitating potential collaborations. The section currently has a few hundred student members, and includes a listserv that allows members to receive information about upcoming workshops and quantitative opportunities. While the current paper focuses on QM opportunities for Canadian psychology, note that there are several associations outside of Canada that host various QM workshops at conventions, in boot camp style sessions, or in a seminar series. Conventions such as Modern Modeling Methods, the APA, and the Association for Psychological Science also offer half or full day workshops on statistical or methodological topics as well as statistical software use. Another example is the extensive workshops put on by Todd Little each summer (see: http://www.statscamp.org/). These workshops have been successful in increasing interest and expertise across a wide array of areas (e.g., Bayesian methods, evaluation, longitudinal analysis, mediation, missing data analysis, multilevel modeling, etc.).

The Role of QM Researchers

This paper has made a number of comments about how researchers and students can benefit from the role of QM researchers. This section is devoted to individuals who are currently

QM researchers, and who we will argue have important roles in the contribution to the field of psychology and not just statistics. QM researchers should not lose sight of the psychology component of one's work and position. This contribution, however, can come in many different forms. QM researchers could act as reviewers for non-QM grant applications and manuscripts to ensure that researchers have given proper thought and treatment to their research design and statistics. Another role is that of a statistical "maven" (Sharpe, 2013), who is someone who seeks "to bridge the communication gap [between QM and non-QM] and navigate the complexities of advanced statistics" (p. 577). Unfortunately these individuals are not always formally recognized but contribute heavily to providing statistical knowledge and aid to other members of their department. Perhaps the specification of alternative positions within institutions is necessary to provide more formal recognition. As an example, teaching or alternate stream positions are becoming more popular. While not for everyone, this is exactly the type of position for which a statistical maven could serve an important role in psychology.

For those interested specifically in QM research, there is still an important role to be played in psychology. The purpose of creating and evaluating advances in statistics is so that they may be used to solve a current data problem plaguing psychological researchers. Creating new procedures with little to no utility in applied research may not offer much in advancing the field. As such, it is important to ensure that QM research is grounded in research practice. Published work on statistical advances should seek to make the procedures as accessible to psychological researchers as possible so that they may be readily implemented. Osborne (2010) argues that, "quantitative researchers are under a moral and ethical imperative to apply their skills in such a way to produce the most defensible, unbiased, generalizable, and applicable results possible" (p. 1). QM research has the potential for an impact on many research areas within psychology in ways that other substantive areas do not. Creating useful statistical and methodological advances in psychology will undoubtedly benefit one's research career and the larger field in which the research occurs. It is worth noting that one of most cited psychology papers of all time (Nosek et al., 2010) is a QM paper in an applied journal (Baron & Kenny, 1986). In fact, it presents no novel research; the goal of the paper was to make mediation and moderation accessible to a wider psychology audience. In summary, QM researchers should consider their role within psychology, not just within their research area. For some it may be through service to the field in the form of consulting, collaboration, and teaching, whereas for others it may be through their innovative, yet useful and accessible statistical contributions.

Discussion

Why are QM skills and statistical literacy so important? Quantitative methods are not going to disappear from psychology any time soon. In fact, methods needed to appropriately analyze the increasingly complicated data being collected create a real need for more advanced quantitative training and graduate programs. Statistics education and literacy help combat a larger systemic issue with reporting practices. The APA publication manual (2010) and many researchers have advocated for a number of improvements to the field such as transparency in reporting and research practices (e.g., Cumming, 2012; Funder et al., 2014; Kline, 2013; Wilkinson et al., 1999) and replication (e.g., Anderson & Maxwell, 2016; Cousineau, 2014; Maxwell et al., 2015; Open Science Collaboration, 2015). We believe that with knowledge of and access to strong quantitative education and training, methodological and research practices can be more open and rigorous, creating a more verifiable and replicable scientific literature.

For this reason, much of the current paper included challenges and opportunities with student training in QM. This focus was intentional as we believe that fields are slow to change, but the change is most likely to be driven by the future researchers whom we train in important issues in quantitative psychology and research practices generally. While only a small percentage of Canadian psychology departments that offer PhDs currently offer a QM specialization, we hope that the current QM programs will continue to grow and that others will emerge. Surveys by Aiken and colleagues (1990; 2008) demonstrated how little change had occurred in graduate training in almost two decades, and that students are only required to take an average of 1.2 years (2.4 classes) of statistics courses. This was replicated by our descriptive study of course requirements; students on average were required to take two courses (totalling one year). However, the number of courses *available* is often higher (1.5 courses more on average), and may be a fair amount higher if the institution has a QM program (6.5 courses more on average). As such, we hope that influential individuals in various institutions see the importance of quantitative training, which can be summed up by the title of Aiken, West, and Millsap's (2009) article, "improving training in methodology enriches the science of psychology."

Conclusion and Recommendations

No field can change overnight. However resistant researchers are to change, the field of psychology requires that some reform is made. Task forces (e.g., APA's task force on statistical inference, Wilkinson et al., 1999), books (e.g., Cumming, 2012; Harlow, Mulaik, & Steiger, 2016; Kline, 2013), and special issues of journals (e.g., *Perspectives on Psychological Science*) have been devoted to the reform of research practices and the use and reporting of statistics. One of the most impactful ways of ameliorating the field is to ensure that the methods and statistics used are transparent and appropriate to the research questions at hand. There exist a large number of resources devoted to how psychologists could change their research practice and strengthen the credibility of psychological research, but we believe that these changes cannot be made without better QM knowledge and training. As such, we conclude with concrete recommendations of ways that will improve QM on both an individual and institutional level.

1) **Team up with a QM person**. If you are lucky, there are QM researchers within your psychology department who may be interested in collaboration and who may be sought by a number of other psychological researchers. Researchers in other fields (e.g., sociology, statistics, business) may also be interested in collaboration and have relevant QM skills.
2) **Build a resource of methodological articles relevant to the types of data that you collect and analyze.** Collect, read, store and reference methodological articles on topics relevant to your research hypotheses and data. If there is a handbook or textbook that targets analyses relevant to your work, invest in it. If you are an editor of a journal, try to include some more methodological papers relevant to your readers. It might be worthwhile to include some special issues that include teaching corner articles that will be helpful for researchers (as an aside these articles are often the most cited articles, increasing the impact factor of the journal).
3) **Consider learning more advanced statistical software.** The newest statistical methods and tools are not often available in commercial software. Open-source software like R (R core team, 2015) allows for users to have instant access to a number of hot-off-the-press tools. Exposure to syntax-based statistical software will also allow more comfort with other types of software and increase the chances of succeeding in understanding and applying appropriate QM. A number of workshops teaching skills in R are available at universities, stats boot camps, and conferences like CPA's annual convention. For those unable to attend these workshops, there are numerous textbooks available to assist

researchers in learning R (e.g., Field, Miles, and Field, 2012 offer a humorous approach to learning R for analyzing psychological data).

4) **Consider QM resources outside of your own department.** Other departments (e.g., sociology, education, statistics, etc.) may offer relevant QM courses. Graduate students interested in advanced QM may take or audit relevant courses not available through their own department. Some provinces (e.g., Ontario) allow graduate students to take relevant courses for credit from other universities without any application process or additional fees for the students. Statistical training for researchers can also be found through workshops on numerous statistical topics. Many of these workshops now have virtual attendance capabilities so that researchers and students unable to travel can still attend and participate in real time. Others may allow researchers to pay a lower fee to provide access to recorded material from a previous workshop. For a list of resources see http://cpa.ca/aboutcpa/cpasections/quantitativemethods/).

5) **Invest in instructors who are passionate about QM.** This starts at the undergraduate level. QM courses are often approached as nothing but a requirement, rather than as an area of interest or learning opportunity. When undergraduates and new graduate students view these courses as a hoop to jump through, it will impact their perceptions of QM and deter them from actively pursuing QM learning and/or careers. Encourage excellent existing faculty or hire an alternative/teaching stream instructor to tackle these courses and inspire future generations of researchers to take interest in QM.

While there are many challenges in building strong QM skills, we hope that researchers see the importance of QM for psychology. With small changes such as those recommended above, we remain confident and optimistic that increasing quantitative literacy in psychology is not only possible, but will result in a stronger psychological science.

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Table 1

QM Course Requirements and Offerings in Canadian Psychology Departments with a PhD Program

	No QM Program		**QM Program**		
Number of Courses	QM Courses Required	QM Courses Offered	QM Courses Required (Non-QM Students)	QM Courses Required (QM students)	QM Courses Offered
1	5 (17.2%)	1 (3.4%)			
2	16 (55.1%)	9 (31.0%)	3 (50.0%)	1 (16.7%)	
3	5 (17.2%)	8 (27.6%)	2 (33.3%)		
4	1 (3.4%)	2 (6.9%)	1 (16.7%)	1 (16.7%)	1 (16.7%)
5		1 (3.4%)			1 (16.7%)
6		5 (17.2%)			
7				2 (33.3%)	
8		1 (3.4%)		1 (16.7%)	1 (16.7%)
9				1 (16.7%)	
10					1 (16.7%)
11					
12					2 (33.3%)
Missing	2 (6.9%)	2 (6.9%)			
Total	29	29	6	6	6
Mode	2	2	2	7	12
Mean	2.07	3.48	2.67	6.17	8.50
SD	.73	1.78	.82	2.64	3.45

Note: No QM program means that the department does not have a QM area of specialization whereas QM program means that the department has one; the total refers to the total number of university departments in each category (with no QM program vs. with QM program). Two departments had missing information because staff did not confirm totals.