# The $Q_1Q_2Q_3$ Workflow for Statistics and Data Science Collaborations

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## Abstract

For today's applied statisticians and data scientists, collaboration is a reality as they often work with domain experts across academic fields, industry sectors, and governmental and non-governmental organizations. To help statisticians and data scientists develop skills and techniques for collaboration, we advance a framework called the *Qualitative-Quantitative-Qualitative* ($Q_1Q_2Q_3$, pronounced "Q-Q-Q") workflow to guide the content of interdisciplinary collaborations systematically. The $Q_1Q_2Q_3$ workflow explicitly emphasizes the importance of the qualitative context of a project, as well as the qualitative interpretation of quantitative findings. We explain $Q_1Q_2Q_3$ and each of its components and provide guidance for implementing each stage of the workflow and teaching it within a statistics and data science collaboration course. Finally, we present data evaluating the effectiveness of teaching the $Q_1Q_2Q_3$ approach to students. We believe that the $Q_1Q_2Q_3$ workflow is an easy-to-implement technique extremely beneficial for statistics and data science education and practice. It honors the subjectivity of the domain expert and the data scientist, helps formalize the role of the human in statistics and data science endeavors, and can be used to weave ethics into each stage of practice so that statisticians and data scientists can successfully transform evidence into action for the benefit of society.

Keywords: statistical collaboration, statistical consulting, statistics education, statistical practice, data science education, data science lifecycle

# 1. Introduction

Statisticians and data scientists have many reasons to collaborate with domain experts across academic fields, industry sectors, and governmental and nongovernmental organizations. One reason to collaborate is to create new knowledge that could not be created alone (Love et al. 2017). According to Vance (2020), a goal of collaborating with a domain expert is to make a deep contribution to their field. No matter what one's personal reasons or goals are, for today's applied statisticians and data scientists, collaboration is a reality as employers seek those with strong collaboration skills (Smaldone et al. 2022). Based on our experience, we believe it is imperative for statistics and data science educators to train students in collaboration and for individuals to develop their personal collaboration skills and techniques.

To emphasize the contribution applied statisticians and data scientists can make on a consultation or to a collaborative project, Vance and Smith (2019) placed Content in the middle of their ASCCR framework for collaboration, which outlines five essential components of collaboration: Attitude, Structure, Content, Communication, and Relationship. But what comprises the content of a statistics or data science collaboration?

Mallows stated, in his 1997 American Statistical Association (ASA) Fisher Memorial Lecture, "The main challenge of applied statistical work is that of taking proper account of contextual issues. Good techniques are not enough; nor are good computer programs, nor powerful theorems. A major intellectual attraction of the discipline is the subtlety of the interplay between the formal statistical procedures and the imperfectly understood substantive questions" (1998,p. 3). He called for the development of a theory of applied statistics—a neat, formal structure—so that it will be easier to teach and more effectively applied. As a starting point he defined The Zeroth Problem to be considering the relevance of the observed data, and other data that might be observed, to the substantive problem. Mallows' thesis is that, before a statistician can formulate a model or analyze the data, her task is to think about the real problem and make judgments as to the relevance of the data in hand—and other data that might be collected—to the problem of interest.

Ograjenšek and Gal (2016,p. 174) wrote that all research is driven by the qualitative 'need to know' that exists in real-world situations or in scientific inquiries. "The 'need to know' dictates how a certain problem may be dealt with: via a quantitative approach and by application of statistical methods (only), via the use of a qualitative approach and related methods (only) or through mixedmethods research, that is, by a combination of quantitative and qualitative reasoning and methods."

On the results of applied statistics projects, Gal and Ograjenšek (2016,p. 204) wrote: "Conclusions have to be presented or reported to clients or stakeholders in ways that they understand and find easy to make sense of, and be congruent with their 'policy language.'" Petocz and Reid described the work of professional statisticians as almost always involving the communication of the results of statistical procedures and investigations and often requiring the education of the domain expert or user of statistical results. They concluded, "While statistics is essentially a quantitative discipline, it contains a necessary core of qualitative components" (2010,p. 272)

Leman et al. (2015) introduced a framework for learning and teaching statistics and data analytics. They stated that in a data analysis project, analyzing the Qualitative issues ($Q_1$) of the context-specific question and data collection method must precede the second layer of analysis dealing with the formal mathematics or computations to address the Quantitative ($Q_2$) issues of the problem. Finally, these numerical summaries must be Qualitatively ($Q_3$) summarized and assessed in a manner consistent with the questions asked in the $Q_1$ phase of the analysis. They concluded that the $Q_1$-$Q_2$-$Q_3$ (QQQ) format can be applied to individual lessons, courses, and entire degree programs.

Vance and Smith (2019) adopted this $Q_1Q_2Q_3$ approach as the primary method for educating and training statisticians and data scientists in the Content of applied projects within their ASCCR framework for collaboration. We believe that $Q_1Q_2Q_3$ is an easy-to-implement technique extremely beneficial for statistical practice and constitutes another step toward forming a theory of applied statistics. It honors the subjectivity of the domain expert and the data scientist (Tanweer et al. 2021), helps formalize the role of the human in statistics and data science endeavors (Vance et al. 2022b), and can be used to weave ethics into each stage of practice (Boenig-Liptsin et al. 2022).

In Section 2 we explain the $Q_1Q_2Q_3$ workflow. Then we provide guidance for implementing each Q in collaborative statistics/data science projects and consultations in Section 3. In Section 4, we describe how we teach $Q_1Q_2Q_3$ in an interdisciplinary collaboration course. We evaluate the effectiveness of this approach for beginning consultants and collaborators in Section 5 and then discuss the implications of the $Q_1Q_2Q_3$ workflow for statistics and data science education and practice in Section 6 before concluding in Section 7.

## 2. Explanation of $Q_1Q_2Q_3$

In our experience, every technical project—be it in applied statistics, data science, physics, engineering, sociology, or the digital humanities—has three components: Qualitative, Quantitative, and Qualitative. These components are interrelated and not always sequential, yet usually follow the order of beginning, middle, and end. Every effective collaboration must start with the Qualitative ($Q_1$) aspects of the project and must also end with the Qualitative ($Q_3$) (Vance and Smith 2019). Statisticians and data scientists have specific expertise in Quantitative ($Q_2$) analyses. Putting these three components together, $Q_1Q_2Q_3$ becomes a simple workflow or lifecycle for statistics and data science practice, a tool for students and practitioners that is potentially more memorable, understandable, and easier for beginners to implement and build upon than more intricate, specialized lifecycles (Boenig-Liptsin et al. 2022; Keller et al. 2020).

An often used lifecycle in statistics education is the PPDAC model, which stands for Problem, Plan, Data, Analysis, and Conclusions (MacKay and Oldford 1994; Wild and Pfannkuch 1999). In our $Q_1Q_2Q_3$ workflow, defining the Problem and creating a Plan for data collection belong in $Q_1$, as do the qualitative aspects of Data collection (e.g., understanding the sources and context of data). Managing, cleaning, and tidying Data and the Analysis of data belong in $Q_2$. Finally, Conclusions form part of our $Q_3$.

We formally define $Q_1Q_2Q_3$ as the interrelated qualitative and quantitative stages of statistics and data science practice necessary for effective statistics and data science collaborations—a three-stage workflow for a collaborative project. Ethical thinking can and should be woven through each stage (Boenig-Liptsin et al. 2022). While the three Qs are presented in sequence and may be performed in order, there is usually iteration between them. For example, results of exploring data in $Q_2$ may necessitate updating the research questions in $Q_1$.

In $Q_1$, the statistician or data scientist should create shared understanding with the domain expert about the goals and context of the project (Vance et al. 2022a), including what the domain problem is, why this problem is important or interesting, how the eventual solution may be implemented ethically in practice, and how the data (if any yet) were collected. In our experience, statistics and data science collaborators—especially those new to the field—typically rush through or even skip

$Q_1$ to get to $Q_2$, where they feel most comfortable. This is a mistake because the context of the domain problem and how data were collected affects all subsequent outcomes, including (but not limited to) potential ethical infractions and the appropriateness of the statistical methods used (Brown et al. 2018). For example, a statistician or data scientist who does not give $Q_1$ its due diligence is at risk of making a Type III error, i.e., the error committed by providing the right answer to the wrong question (Kimball 1957).

In $Q_2$, the statistician or data scientist applies Quantitative techniques to analyze the data to answer the $Q_1$ domain question(s). During $Q_2$, analysts prepare the data (e.g., clean and tidy the data), explore and summarize data (e.g., visualize the data), formulate models, perform statistical inference, and summarize quantitative findings in ways that respect ethical guidelines, such as assuring data privacy. Crucially, part of the $Q_2$ stage is determining analytically and quantitatively whether the data collected are appropriate for solving the problems from $Q_1$. For example, a $Q_2$ analysis might suggest that a variable not fully discussed in $Q_1$ is an important moderating or mediating variable. The analyst may need to clarify additional $Q_1$ issues with the domain expert before returning to $Q_2$.

The final stage of our workflow, $Q_3$, is the concluding Qualitative component of a collaborative project. To fully complete this stage, the statistician or data scientist creates a shared understanding with the domain expert about how the results or findings from $Q_2$ answer the questions from $Q_1$, how the $Q_2$ findings can be summarized into recommendations, and how to create a plan for action to implement these recommendations responsibly and ethically. Gal and Ograjenšek (2016,p. 204) write of the importance of qualitatively summarizing the results of applied statistics projects: “Conclusions have to be presented or reported to clients or stakeholders in ways that they understand and find easy to make sense of, and be congruent with their ‘policy language.’” We believe that statisticians and data scientists who desire to make a positive impact on society should also take the further steps of working with the domain expert to provide recommendations and a plan for action based on evidence from $Q_2$. Such recommendations and plans naturally stem from a mindset of transforming evidence into action for the benefit of society (Olubusoye et al. 2021).

Notably, ethical thinking is woven through the stages as suggested by Boenig-Liptsin et al. (2022), who proposed a six-stage lifecycle centered around ethical thinking. Of their “Ethos Lifecycle’s” six stages, the first two—Question/Problem Identification and Data Discovery—map onto $Q_1$, the middle two—Exploratory Data Analysis and Modeling—map onto $Q_2$, and the final two—

Interpretations/Conclusions/Predictions and Communication/Dissemination/Decision Making—map nicely onto $Q_3$. Users of the Ethos Lifecyle can think about the social and ethical contexts of each stage through four social-science-based conceptual lenses (Positionality, Sociotechnical Systems, Power, and Narratives) (Boenig-Liptsin et al. 2022).

Figure 1 depicts the stages of $Q_1Q_2Q_3$ and their interrelationships. The stages are initiated in order, i.e., collaborative projects start with $Q_1$, move into $Q_2$, and end with $Q_3$. The stages also influence one another non-sequentially. For example, when interpreting findings ($Q_3$), the collaboration team may need to revisit the original goals and context of the problem ($Q_1$) or conduct additional quantitative analyses ($Q_2$).

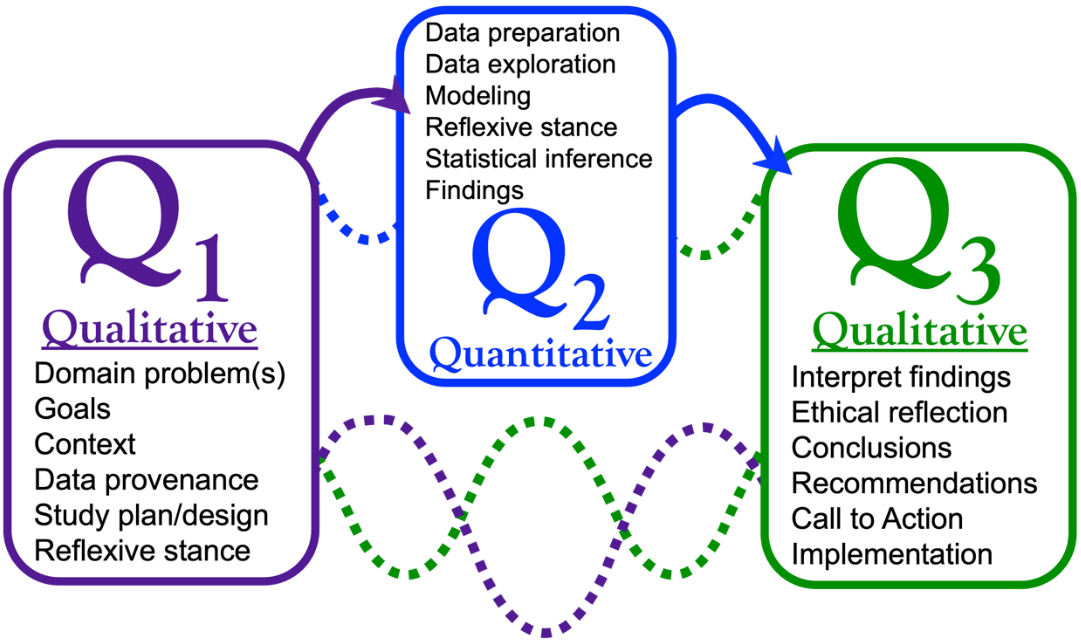


**Figure 1.** The $Q_1Q_2Q_3$ workflow for effective statistics and data science collaborations iterates between the qualitative and quantitative stages of a project.

An analogy for the $Q_1Q_2Q_3$ workflow is the hero's journey (Campbell 2003) in which an interdisciplinary collaboration is like an epic adventure, and both statistician/data scientist and domain expert are the heroes. The hero's journey consists of three stages: Departure, Initiation, and Return, which parallel the three stages of $Q_1Q_2Q_3$.

1. *Departure ($Q_1$).* The heroes live in the ordinary world and receive a call to adventure. The ordinary world is one of ignorance, without answers to research questions or data-driven ways to make sensible business and policy decisions. The call to adventure is the problem that the domain expert presents to the statistician/data scientist.

2. *Initiation ($Q_2$).* The heroes traverse the threshold to an unknown world where they face trials. In our analogy, the unknown world is the world of quantitative reasoning, and the trials are the quantitative analyses that must be performed.
3. *Return ($Q_3$).* The heroes again traverse the threshold between the worlds, returning to the ordinary world with gained treasure. The treasure is knowledge that demands a call to action to use their new knowledge to help others and benefit society.

Through their collaborative journey, the heroes are transformed and gain wisdom. In effective collaborations, the statistician/data scientist and domain expert gain expertise in both the research domain and quantitative methods.

An example of the $Q_1Q_2Q_3$ stages in a data science research project is when a team of statisticians (including this paper's first author) and a historian collaborated to predict where enslaved people came from within Africa before they were forcibly shipped across the Atlantic Ocean (Wiens et al. 2022).

1. *$Q_1$:* Armed conflicts (wars) in the Kingdom of Oyo (modern-day Nigeria) from 1817–1836 resulted in 121,000 enslaved people sent in slave ships to the Americas. While historians have a good record of where the enslaved *went* across the Atlantic, they have no records of where they were from *within* Africa. The team compiled data on historical trade routes and the time, place, and severity of armed conflicts in Oyo.
2. *$Q_2$:* The team used kriging and a Markov decision process to simulate the capture and transport of the enslaved to ports of departure. The researchers aggregated the simulations to predict the conditional probabilities of the likely origin locations of the enslaved, which were then visualized on maps of the region (see bit.ly/Oyoorigins).
3. *$Q_3$:* These maps help historians better understand the history of Africa and the entire Atlantic world, whereby the ocean connects, rather than disconnects, Africa, the Americas, and Europe. The paper concludes with a call to action for historians to generate new data about the transatlantic slave trade and to collaborate with statisticians and data scientists to analyze these data to gain valuable historical insight.

Understanding the $Q_1$ historical context of how people became enslaved because of internal conflicts/wars and how they were transported to ports of sale was crucial for the statisticians to develop appropriate $Q_2$ statistical models and algorithms. Similarly, understanding the $Q_2$ models and their limitations was vital for the collaboration team to make appropriate $Q_3$ conclusions and recommendations. Completing all stages of $Q_1Q_2Q_3$ enabled the team to maximize the potential impact of their work.

# 3. Implementing $Q_1Q_2Q_3$ in Statistical Collaborations

The $Q_1Q_2Q_3$ workflow naturally fosters a reflexive stance (D'Ignazio and Klein 2020). By placing importance on both qualitative and quantitative aspects of projects, $Q_1Q_2Q_3$ users have designated times to pause and consider at key decision points how their own assumptions, experiences, and relationships influence the collaborative project. According to Tanweer (2021,p. 13), "A reflexive stance acknowledges that subjectivity and bias are not aberrations that can ever be fully eradicated from research but inherent aspects of human inquiry that should be acknowledged and accounted for." Adopting a reflexive stance is one way ethical thinking can be woven into every aspect of $Q_1Q_2Q_3$.

In our experience, most statistics and data science collaboration projects span multiple meetings, and $Q_1Q_2Q_3$ is a useful workflow for the *project*, not a structure for an individual meeting. To structure individual meetings, we recommend implementing the POWER structure (Alzen et al. 2024; Zahn 2019). The "W" of the five-part POWER meeting structure stands for "Work," and the $Q_1Q_2Q_3$ workflow can guide this work. During initial meetings, the collaborative statistician or data scientist typically works with the domain expert to create shared understanding of the domain expert's goals, problem, and data ($Q_1$). In a second meeting, they typically work on explaining a statistical analysis ($Q_2$) or asking great questions to create an appropriate model for the data. Later, or during a third meeting, they may focus on interpreting the results of the statistical analyses, developing recommendations, and initiating a plan to implement their recommendations ($Q_3$). We provide details on implementing $Q_1Q_2Q_3$ below.

## 3.1 Implementing $Q_1$

To successfully implement $Q_1$, the statistician or data scientist should create shared understanding (Vance et al. 2022a) about the domain issues that will impact the $Q_2$ analyses and the $Q_3$ interpretations, recommendations, and plans for action. What are these important issues? Peterson et al. (2022) have provided eight guidelines, a template, and a table of 23 vital questions for creating a scope of work for a collaborative project, i.e., guidance for the $Q_1$ activities—before conducting $Q_2$ analyses—of understanding the problem background and specific research questions, the data structure and study design, the desired statistical analyses, the primary outcome and potential explanatory variables, tables and figures to be produced, and mutual expectations of final deliverables for the project.

Also focused primarily on the $Q_1$ stage, Cressman and Sharp (2022) detailed how to create a statistical analysis plan at the beginning of a project for researchers to organize their knowledge about their research questions and experimental design to more easily recognize and choose the appropriate statistical analyses. They provided seven primary questions and 40 additional subquestions to ask the domain expert before proceeding to conduct the $Q_2$ analyses.

Since 2019 we have educated students to ask about—at the beginning of their collaborative projects—the following seven qualitative aspects of the project and to verify with the domain expert in writing their understanding of the answers.

1. What is the domain problem?
2. Why is the problem important or interesting? And, to whom?
3. How will the eventual solution be used?
4. What potential data could solve the domain problem? (i.e., what data, if it were available and accessible, would help answer the underlying questions?)
5. The Five Ws and one H of the actual data, if any have been collected (i.e., study design and data provenance):
    a. What data were collected?
    b. Who or what collected the data?
    c. Why, and for what purpose, were the data originally collected?
    d. When were the data collected?
    e. Where were the data collected?
    f. How were the data collected?
6. What may be the qualitative relationships between variables, for variables both observed and unobserved?
7. Which types of statistics or data science analyses or techniques would be most useful to the domain expert?

In our experience, creating shared understanding around the first two questions of understanding the domain problem and why it is important or interesting and to whom (i.e., who are the stakeholders who care about the problem and why do they care?) will provide a strong motivation for the statistician/data scientist to become engaged in the project. We find that we are able to do better statistics and data science and make a deeper contribution to the domain when we too care about the project. Additionally, conversations around these first two questions can help build strong relationships. According to Vance (2020), making a deep contribution and creating a strong relationship with the domain expert are *the* two terminal goals of any collaboration.

Understanding how an eventual solution may be used or implemented in practice can guide the statistician/data scientist to choose the most appropriate quantitative methods analytically and ethically. For example, a very high stakes "life or death" project may demand the most sophisticated, rigorous analysis possible, whereas a simple *t*-test or descriptive summary may be the best analysis for other projects. Stallings (2014) wrote about the errors collaborative statisticians make when they conduct an overly complicated analysis that is hard for the domain expert to understand or explain to others and is therefore not used. He concluded that simpler analyses are often more impactful than complex ones.

Discussing potential data—before discussing the actual data—is an exercise that can help clarify the domain problem (e.g., perhaps the actual underlying domain problem is that the available data are imperfect or inadequate). It may be that the solution to the domain problem becomes simplified by collecting new data and that the domain expert and data scientist overlook this by focusing only on data already collected. On the other hand, the impossibility of collecting certain data or incorporating existing data into the analyses can illuminate the intricacies of the domain problem and help guide the collection or analysis of alternative data (Keller et al. 2020).

Understanding what the actual data are, how they were collected, and for what original purpose (i.e., data provenance) will help the statistician appropriately explore, visualize, model, and analyze the data and interpret the results. Sometimes a barrage of questions from the statistician can be construed as "impertinent" (Lurie 1958), and the domain expert may resist thoroughly discussing the information relevant to $Q_1$ because they feel it is an inefficient use of time or unnecessary for the statistician to complete their task. We recommend using the strategies of "asking great questions" (see Vance et al. 2022b) to use these questions as an opportunity to strengthen the interpersonal relationship. One of the strategies is to preface questions with their intent. For example, to start a discussion about the experimental design (Question 5, part f), the statistician may say, "So I can better understand the experiment and appropriately model the data, how were the treatments assigned?" By prefacing questions with the intent, the statistician explains to the domain expert why it is worth their time to discuss the $Q_1$ components of the problem. Another strategy to encourage discussion about $Q_1$ aspects of the project is to include the $Q_1$ questions in the meeting agenda, especially when it is the first meeting between the statistician and domain expert. For an example initial meeting agenda, see bit.ly/gdoccollabtemplate.

Question 6 is a precursor to the $Q_2$ activity of modeling the data, as it is essential for identifying confounders, mediators, and effect modifiers (a.k.a. moderators or interactions). A helpful strategy for answering this question is to work with the domain expert to draw a causal diagram with arrows depicting the relationships between variables (Pearl 1995). The three diagrams in Figure 2 depict simple examples of causal diagrams for a confounder, effect modifier, and mediator.

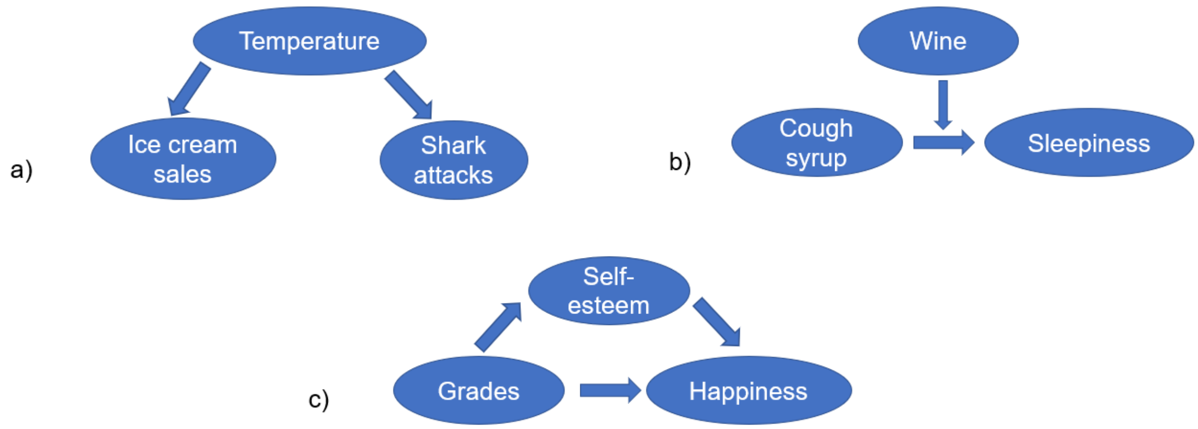


**Figure 2.** Example causal diagrams with the dependent variable/outcome in the bottom right, the primary predictor of interest in the bottom left, and the confounder (a), effect modifier (b), or mediator (c) on top. These diagrams are helpful tools for completing the $Q_1$ stage of collaboration.

Finally, discussing at the beginning of a project ($Q_1$) which types of analyses will be most useful to the domain expert is a key component of creating a scope of work (Peterson et al. 2022) or a statistical analysis sketch (Cressman and Sharp 2022). Are certain techniques frowned upon by the domain expert or their domain? Could new statistics or data science methods be developed to more usefully answer the domain question? Statisticians and data scientists have the potential to drive collaborative projects to develop new technical methods tailored to better answer the particular domain questions. However, if the domain expert does not understand or cannot defend the choice of a specific statistical technique, that technique may not be useful, and a simpler or more familiar method may need to be used. If the simpler method is not appropriate for the problem and the data, the more advanced method should be used in $Q_2$ with sufficient time spent explaining the new method to the domain expert in $Q_3$.

## 3.2 Implementing $Q_2$

Statisticians and data scientists are likely most familiar and most comfortable with the $Q_2$ stage of $Q_1Q_2Q_3$ as this stage is often the sole focus of standard statistics or data science courses. Even though $Q_2$ is a technical, quantitative stage, nuanced choices are needed to decide which methods to apply and how to interpret their results and evaluate their success. Here, we highlight strategies and resources for making these choices.

A simple way to decide among models is to label their use as descriptive, inferential, or predictive (Shmueli 2010). Then, analysts choose a model with a use that aligns with the goals and data discussed in $Q_1$. Using this strategy to categorize models also aids in explaining models to domain experts and enables analytic pivots when needed. For example, if it has been determined in $Q_1$ that the data collected are not sufficient to answer the original (inferential or predictive) research questions, the analyst can still help the domain expert describe the data using summary statistics and visualizations. There may still be an important narrative to be told with the existing data, including associations within the data, even if the data are not generalizable to explain phenomena (i.e., inference of model parameters) or to make out-of-sample predictions.

For a more advanced approach to choose among models during $Q_2$, we suggest the following two references. Dwivedi (2022) refines the classification of descriptive, inferential, and predictive models into six categories depending on the study objectives and provides 10 essential steps to be reported for statistical analyses. Dwivedi and Shukla (2020) summarize 38 essential steps of data analysis for common study designs and objectives. They provide checklists for the reporting of research design with 10 individual checks, assessing data analysis practices with 10 individual checks, and for conducting evidence-based statistical analyses for 11 common study designs and objectives (73 total checks).

As models are chosen and fit to the data during $Q_2$, we recommend keeping in mind the Predictability, Computability, and Stability (PCS) principles of veridical data science proposed by Yu and Kumbier (2020) to create a common culture and assure truthful findings from data. We briefly summarize each principle:

- Predictability: a model's ability to accurately predict new observations. Measures of model *prediction* can serve as tools for evaluating, improving, and applying analytic methods. Predictability serves as a reality check for the quantitative methods.
- Computability: a model or algorithm's computational efficiency and scalability. For example, available computing power may directly influence how and where data are collected, stored, shared, processed, and summarized. Computability ensures results are obtainable.

- Stability: whether another researcher making alternative, appropriate decisions would obtain similar conclusions. Stability ensures the reproducibility of results relative to human decisions.

The PCS principles describe a common value system for implementing $Q_2$. Statisticians and data scientists should consider, measure, and report each element of PCS in their $Q_2$ analysis so that their results have the potential to be “responsible, reliable, reproducible, and transparent … across fields of science” (Yu and Kumbier 2020,p. 3920). Note that although we discuss PCS in the context of $Q_2$, these principles should be upheld throughout $Q_1Q_2Q_3$.

## 3.3 Implementing $Q_3$

$Q_3$ is the final stage of $Q_1Q_2Q_3$, where a statistician or data scientist can make the most impact on the outcomes of the project. A p-value from an analysis is not itself an answer to a research question; p-values alone will not help anyone make a decision. In $Q_3$, the statistician or data scientist effectively translates the quantitative evidence from $Q_2$ into answers to the $Q_1$ research or policy questions. To achieve higher impact, statisticians or data scientists should summarize the $Q_2$ findings into recommendations and create a plan with the domain expert to implement these recommendations. As a guide for completing $Q_3$, we outline seven questions for statisticians and data scientists to ask themselves and the domain expert.

1. Qualitatively, what do the results mean?
2. What are the constraints, limitations, and assumptions of the quantitative methods? What conditions are necessary for the results to be valid?
3. How can we visually display and communicate the results of the analysis in a way the domain expert and their stakeholders (i.e., advisor, manager, peers, funders, etc.) will understand?
4. What are the answers to the domain experts’ questions and how are these relevant to the research/business/policy goals?
5. What are the implications of the answers, including ethical implications?
6. What actions do we recommend should be taken?
7. What is our plan for action to implement these recommendations?

In the $Q_3$ stage, it is crucial that the statistician/data scientist and domain expert have clear communication and develop shared understanding about the results (i.e., questions 1–6 above). To achieve this, we summarize five strategies. First, results should be explained in language that is accessible to the domain expert. Second, the statistician should be intentional about providing the domain expert multiple opportunities to speak and ask questions throughout meetings. For example, periodically checking in with the domain expert by asking “What can I clarify?” or “What can I explain further?” often and after each explanation can be helpful. Third, the statistician can ask the domain expert how they would explain the results in their own words. For example, the statistician might say, “I want to make sure that I have explained these results clearly. To check that I have done that, could you tell me how *you* would explain these results to your stakeholders?” Fourth, the statistician and domain expert can brainstorm together what actions or implications the results suggest. Lastly, all results, findings, conclusions, implications, and recommendations should be written up clearly in a document and shared between the domain expert and statistician.

Throughout $Q_3$, the statistician or data scientist will benefit from adopting the attitude of a collaborative relationship (Halvorsen et al. 2020) in which the statistician considers themselves to be on the same team as the domain expert—just one of many experts in the room—such that the statistician succeeds when the domain expert succeeds. The collaborative statistician/data scientist believes that $Q_3$ is not about showing off their quantitative expertise, rather, it is about helping the domain expert make a good decision and transforming results into action for the benefit of society.

In our experience, $Q_3$ is rarely completed fully; domain experts and statisticians/data scientists seldom co-develop a plan for implementing their recommendations. This is a missed opportunity because we believe that statisticians and data scientists have the potential to drive advances to benefit society. Indeed, former ASA president Phillip Hauser stated that statisticians have an *obligation* to play significant roles in society (Hauser 1963).

To achieve this potential impact, we recommend being especially mindful of question 3 from $Q_1$ about understanding (at the beginning of the project) how the eventual solution might be used and then following through with the domain expert (at the end of the project) to develop a plan for action. Even better would be to meet with policy makers/implementers before or during the design of the study to understand what kind of evidence would be persuasive (Hartman et al. 2020), which is a best practice in clinical trials design as recommended by The Global Health Network (2023). Statisticians and data scientists can also choose to pursue the collaborative projects that have the most potential to result in positive impact. A step in the right direction for such impact is the ASA’s Influencing Discovery, Exploration, and Action (IDEA) Forum, which helps build strategic partnerships with leaders from academe, government, and industry to grow the influence of statisticians and drive innovative solutions to problems of the world community (Ensor and LaLonde 2023).

# 4. Teaching $Q_1Q_2Q_3$ for Statistics and Data Science Collaborations

We teach the $Q_1Q_2Q_3$ workflow in a 15-week-semester-long "Statistics and Data Science Collaboration" course to senior undergraduate statistics and data science (SDS) majors, professional masters SDS students, SDS Ph.D. students, and Ph.D. students in other quantitative fields. Applying aspects of a community of practice approach to teaching and learning (Alzen et al. in press), we use Team-Based Learning to flip the classroom (Vance 2021) and engage students in a five-stage pedagogical process: Prepare, Practice, Do, Reflect, Mentor (LeBlanc et al. 2022). Students *Prepare* by reading about $Q_1Q_2Q_3$ outside of class, *Practice* applying the $Q_1Q_2Q_3$ workflow on homework and in-class exercises, implement (*Do*) $Q_1Q_2Q_3$ on three real collaboration projects (see Alzen et al. (2024) for a description of typical projects, which range from straightforward to complex), *Reflect* on their learnings, and provide feedback and coaching to peers (*Mentor*) on their use of $Q_1Q_2Q_3$. Below we provide more details specific to teaching $Q_1Q_2Q_3$, with links or references to instructional materials in the appendices.

### *Prepare*

Students prepare to implement $Q_1Q_2Q_3$ in actual collaborations starting in week 2 of the course by reading the ASCCR framework paper (Vance and Smith 2019) and answering a few general homework questions about the framework. In week 3, students read a four-page handout specifically about $Q_1Q_2Q_3$ (Vance 2019), which will be augmented or replaced in future semesters by reading Sections 2, 3, and 7 of this paper. Then in week 5, students read about Type III errors in the classic paper "Errors of the Third Kind" (Kimball 1957). Near the end of the semester (week 13), students are exposed to a lecture and discussion of an application of $Q_1Q_2Q_3$ for oral presentations we call "QMatrix" (Trumble et al. 2022).

### *Practice*

Early in the semester (weeks 3–4), students observe a real collaboration meeting and—as part of a homework assignment—summarize the $Q_1$, $Q_2$, and $Q_3$ aspects they observed. Initial collaboration meetings often only get through $Q_1$, which is a surprising and valuable lesson for students. Also during weeks 3–4, students practice asking $Q_1$ questions during in-class role-plays of meetings.

During week 5, students complete a homework assignment in which they generate an example of a Type III error, ideally one they made or noticed someone else make. Alternatively, the example could be from popular culture, i.e., a Type III error committed by someone in a book or movie. In class later the same day the assignment is due, students work in their (permanent, 3–5 person) teams to discuss Type III errors and generate strategies to avoid them. (See Appendix A for these in-class team exercises.) $Q_1Q_2Q_3$ is not explicitly mentioned in the exercises, yet most teams identify "creating shared understanding of $Q_1$ issues" as a good strategy for avoiding Type III errors.

In weeks 13 or 14, students attend any quantitative presentation (e.g., a statistics departmental seminar) and complete a homework assignment in which they track how much time the presenter speaks about $Q_1$, $Q_2$, and $Q_3$ (see Appendix B).

*Do*

During weeks 4–16 (including finals week 16), students work in pairs on three real collaboration projects. Students use a meeting notes template (bit.ly/gdoccollabtemplate), which reminds students about asking $Q_1$ questions. Students submit a report about their initial project meeting and a final project report, both of which follow essentially the same format of "summarize $Q_1$, $Q_2$, and $Q_3$" (see Appendix C for the final report prompt). During weeks 15–16, pairs of students use the $Q_1Q_2Q_3$ workflow to help organize their final project presentations.

*Reflect*

Reflection is woven into most homework assignments (including final project presentations) and in-class exercises. Specifically, students are asked to reflect on each of their collaboration projects and, in week 14, on the ASCCR framework. Sprinkled throughout the course are discussions of active projects, which primarily focus on $Q_1$ and $Q_2$.

*Mentor*

Students typically work in pairs on their collaboration projects, which provides peer mentoring opportunities. In addition to projects and in-class project discussions, students may mentor their peers during occasional (1–2 times in the latter half of the semester) Video Coaching and Feedback Sessions (VCFS). During VCFS, students provide feedback and coaching (i.e., mentoring) to their peers about many aspects of the video-recorded collaboration meeting, including $Q_1Q_2Q_3$.

# 5. Assessing the Success of the $Q_1Q_2Q_3$ Approach

On a short, outside-of-class survey administered during the last week of the semesters, four cohorts of students in the course described above were asked a quantitative, six-point Likert-scale question, “How valuable do you think the $Q_1Q_2Q_3$ approach will be throughout your career?” The most recent three cohorts of students were also asked a qualitative follow-up question, “Has learning about the $Q_1Q_2Q_3$ approach strengthened your ability to successfully complete statistics or data science collaboration projects? Why or why not?”

Most students completed the survey and agreed to allow their responses to be aggregated for research purposes. The number of students answering the quantitative question was n = 21 of 21 students in Fall 2021, n = 12 of 12 students in Spring 2022, n = 11 of 15 students in Fall 2022, and n = 10 of 20 students in Spring 2023. Most of these students (85%, 28 of 33 respondents excluding Fall 2021 students) also responded to the qualitative follow-up question. The instructor during Fall 2021 and Spring and Fall 2022 was this paper’s first author. The instructor during Spring 2023 was not one of this paper’s authors. Students in that semester engaged in ostensibly the same pedagogical process as described in Section 4, though they only collaborated on one or two projects (instead of three), did not engage in the “QMatrix” activities, and did not participate in Video Coaching and Feedback Sessions. Figure 3 shows the students’ responses to the quantitative question on a six-point scale of Not valuable at all – Slightly valuable – Somewhat valuable – Moderately valuable – Very valuable – Extremely valuable.

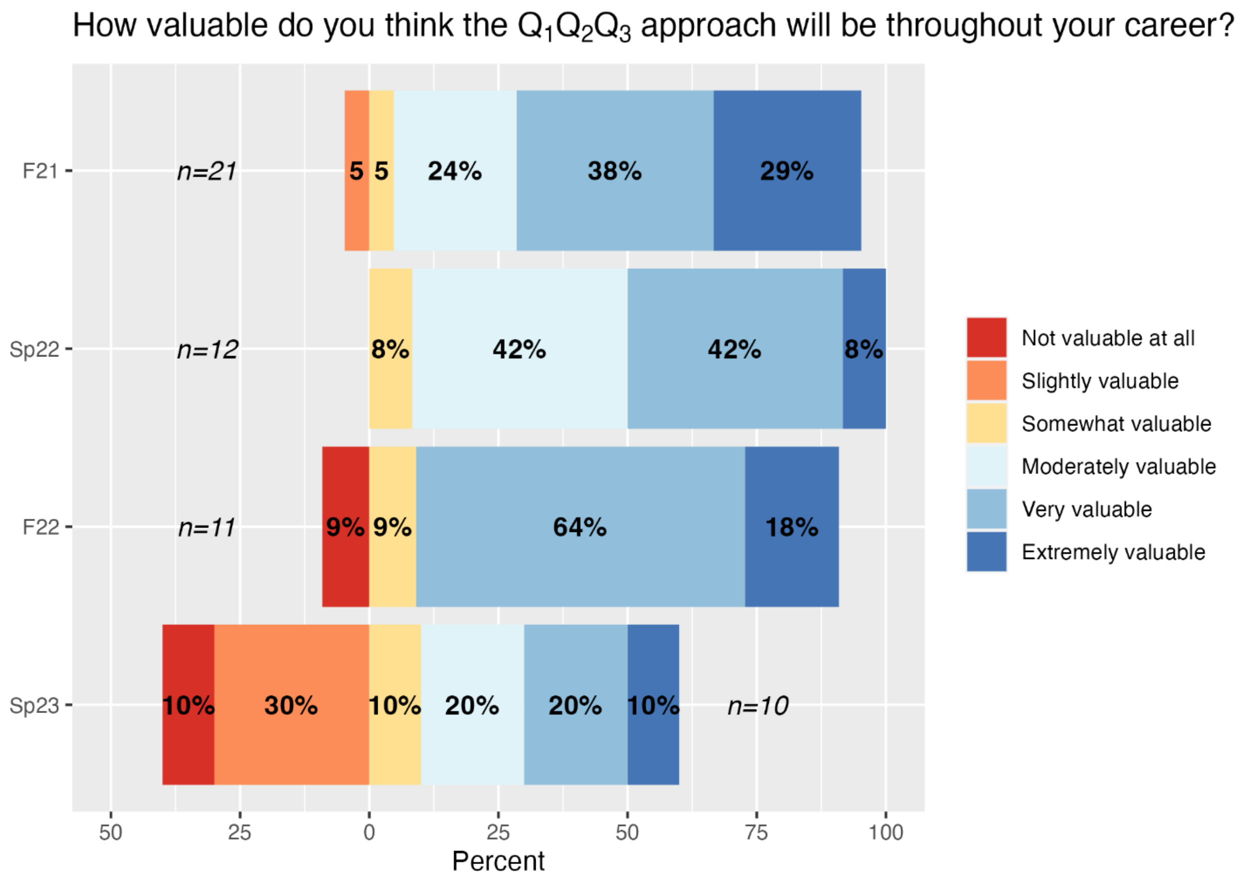


**Figure 3.** The stacked bar chart shows the percentage of responses on a six-point Likert scale for four semesters of students in an interdisciplinary collaboration course.

In each semester, at least one student (19%) was enthusiastic about $Q_1Q_2Q_3$, responding that this workflow would be "Extremely valuable" in their careers. A representative qualitative follow-up response from this group from Spring 2023 was: "Learning about the $Q_1Q_2Q_3$ approach has helped me to spend more time understanding the domain problem from a qualitative standpoint and making sure I ask the right questions before moving on with the quantitative portion of the work."[1]

While not as enthusiastic as a few, most students appreciated $Q_1Q_2Q_3$, responding that it will be "Very valuable" (41%) or "Moderately valuable" (22%) in their careers. A representative "Very Valuable" follow-up response from a student in Spring 2023 was:

> *"I think that emphasizing the domain problem like in $Q_1Q_2Q_3$ is extremely important because it's hard to remember to focus on the domain problem*

[1] Every student quote in this paper comes from a unique student, i.e., the 13 qualitative quotes are from 13 students.

*sometimes when you're more focused on the math and the data. Personally, I'm motivated to do data science because of the domain problem, so I've always placed equal emphasis on both. But I think that this approach was really beneficial for my classmates."*

A student responding "Moderately valuable" in Spring 2022 wrote: "Yes, I think this approach has strengthened my ability to complete collaboration projects because it has forced me to slow down and fully understand the research goals before trying to interpret data."

One student in each semester responded that they expected $Q_1Q_2Q_3$ to be "Somewhat valuable" (7%) in their careers. A student from Spring 2022 who seemed to forget that $Q_1$ is Qualitative, $Q_2$ is Quantitative, and $Q_3$ is Qualitative responded "Somewhat valuable" and wrote: "Not really - I think for my purposes I would change the order to $Q_2$, $Q_1$, $Q_3$. I think it's more natural to discuss the bigger qualitative picture before diving into the quantitative components of the project."

The rest of the students (11%) did not expect $Q_1Q_2Q_3$ to be especially valuable in their careers, responding that it would be "Slightly valuable" (7%) or "Not valuable at all" (4%). Based on their responses to the qualitative follow-up question, most of these students seemed to have a faulty understanding of $Q_1Q_2Q_3$ and/or confused it with a structure for individual meetings rather than as a workflow or life cycle for an entire project. A student from Spring 2023 who responded "Slightly valuable" wrote: "It's good to have a structure somewhat, but flexibility is better." A student from Fall 2022 who responded "Not valuable at all" also confused $Q_1Q_2Q_3$ with a meeting structure: "It really didn't, in my opinion how a meeting should be structured should be organized based on the problem at hand. $Q_1Q_2Q_3$ makes me feel like I'm just going through the motions rather than actually learning or doing anything."

Wilcoxon Rank Sum tests performed in R (R Core Team 2023) to test for pairwise differences in the distributions of student responses by semester showed that students in Spring 2023 rated $Q_1Q_2Q_3$ about one unit less valuable than students from the other three semesters and that students in Fall 2021 rated $Q_1Q_2Q_3$ about one unit more valuable than students in Spring 2022 (and also Spring 2023). However, only the difference in the distribution of student ratings between Fall 2021 and Spring 2023 was statistically discernible ($p = 0.012$). All other p-values were greater than 0.1.

It is not particularly surprising to us that students from Fall 2021 and Spring and Fall 2022 (who were taught by this paper's first author) generally rated learning about $Q_1Q_2Q_3$ to be valuable and that their ratings were higher than the students in Spring 2023 who were taught by a different instructor. This result does highlight the importance of the instructor's own grasp of and enthusiasm for $Q_1Q_2Q_3$ when teaching this workflow; a lack of enthusiasm for the topic could also explain the much lower response rate in Spring 2023, which was 50% compared to 100%, 100%, and 73% for the other semesters. Despite this, the respondents from Spring 2023 were still generally positive about $Q_1Q_2Q_3$. Additional discussion emphasized by qualitative quotes from students about $Q_1Q_2Q_3$ follows in Section 6.

# 6. Discussion

## 6.1 $Q_1Q_2Q_3$ Is a Simple yet Versatile Workflow

A student from Fall 2022 commented:

> *"Learning about $Q_1Q_2Q_3$ approach has strengthened my ability to complete data science projects. It is a simple, versatile framework that balances background information, the technical information, and the conclusion. It keeps your project 'grounded' to what is most important to discuss."*

In our view, the value of $Q_1Q_2Q_3$ does indeed stem from its simplicity, its universal applicability to every data science project, and its versatility. Another student from Fall 2022 commented: "[$Q_1Q_2Q_3$] gives me a nice flow to go about completing a project. The order is very logical and is set up in such a way that it is difficult to make any type of error."

Our goal for using $Q_1Q_2Q_3$ is to teach/remind statistics and data science collaborators about three high-level concepts:

1. Create shared understanding of the context of the problem, questions, and data ($Q_1$) before beginning the quantitative analysis ($Q_2$).
2. Be sure to translate the findings from the $Q_2$ analysis into meaningful answers (conclusions) to the original questions ($Q_3$).
3. For increased impact of your work, develop recommendations with the domain expert and a plan for action ($Q_3$).

A quote from another student from Fall 2022 illustrates these first two points:

*"I think it has because [$Q_1Q_2Q_3$] gives a good framework to go about the work. It is beneficial to really flesh out the qualitative goals initially to make sure that subsequent quantitative work is worth the time (i.e. even answers the question). Having a thorough understanding of what the results mean is also beneficial."*

We also use $Q_1Q_2Q_3$ because of its versatility to provide a starting point from which to think about and explore more complex concepts and data science lifecycles such as understanding the provenance of data, adopting a reflexive stance in our data science work, thinking ethically throughout a project, ensuring the reproducibility and computability of our work, testing assumptions and validating conditions of our analyses, and additional aspects of statistics and data science practice described in Section 3.

## 6.2 $Q_1Q_2Q_3$ Is Helpful in the Classroom

$Q_1Q_2Q_3$ helps instructors teach collaboration by creating a shared vocabulary with students that enables discussion about the importance of context and qualitative issues when analyzing data and how the end goal of a collaboration is the impact made rather than just the analysis (Vance 2020). A student from Fall 2022 commented: "Yes, [$Q_1Q_2Q_3$] has given me a named format with which I can identify the stage of a project I might enter at and it gives me a way to describe the progress of a collaboration to the DE [domain expert]."

Using the workflow also creates spaces for the instructor to add lessons to address learning outcomes that might not naturally fit elsewhere. For example, in the interdisciplinary collaboration course described in Section 4, a unit of a reading, classroom exercises, and discussion of ethics occurs during Week 11. This unit on ethics in data science builds upon students' own collaboration experiences and builds upon their familiarity with the $Q_1Q_2Q_3$ stages. Similarly, a unit on reproducible research could fit as part of a discussion of $Q_2$, as does the classroom discussion of technical data science issues from ongoing students' projects. The instructor could say, "Let's talk about $Q_2$" to introduce a time for such a discussion of $Q_2$, which naturally presupposes a sufficient understanding of $Q_1$ and can foreshadow what the student and domain expert will do with the analyses in $Q_3$.

## 6.3 Four Reasons the $Q_1Q_2Q_3$ Workflow Provides Value and Benefits for Collaborative Projects

First, while the modern student's statistics and data science education is still predominantly focused on the theory, methods, and applications of statistics and data science (i.e., $Q_2$), the $Q_1Q_2Q_3$ workflow emphasizes the importance of qualitative issues in collaborative data science projects. This is important because, as Ograjenšek and Gal (2016,p. 176) wrote: "Continuing to exclude qualitative methods and thinking from statistical training may hamper our ability to effectively collaborate and communicate with diverse clients and audiences about the contribution and value of statistics and statistical investigations." $Q_1Q_2Q_3$ helps students appreciate the value of understanding the qualitative. A student from Fall 2022 commented: "Yes, [$Q_1Q_2Q_3$ is valuable] because it forced me to ensure I understood the discipline and research problems before starting the code/statistics portion." A student from Spring 2022 commented: "[$Q_1Q_2Q_3$] is helpful for figuring out what exactly you want to know before diving into existing data/ data collection."

Second, $Q_1Q_2Q_3$ provides a framework for statistics and data science collaborators and educators to address $Q_2$ on its own in an exposition of a specific statistical method, in relation to $Q_1$ while discussing what qualities make a dataset appropriate for use with the method, or in relation to $Q_3$ while discussing the limitations of what could be concluded if that method were used. Meng emphasized this point that "Qualitative and quantitative thinking co-exist and interact at all research stages, and therefore, there should be an on-going emphasis of this interplay in all statistical education and beyond." (2016,p. 187). Meng called for codifying the interplay between the qualitative and quantitative as the "Q-q dynamic, with Q representing the thinking process receiving more emphasis at a particular stage. When and which 'q'–quantitative or qualitative–deserves to be capitalized will depend on the context" (2016,p. 187). A student's comment from Fall 2022 shows how the "Q-q dynamic" can be deduced from study of $Q_1Q_2Q_3$: "I believe the [$Q_1Q_2Q_3$] approach is essential, and it reminds everyone that statistical collaboration demands the marriage of quantitative and qualitative skills."

Third, the $Q_1Q_2Q_3$ workflow reduces pressure on students who mistakenly believe that they must have ready $Q_2$ answers for the domain expert during their initial collaboration meeting. Understanding that the initial meeting should be primarily focused on $Q_1$ enables students to think more deeply about the project's context determines the appropriate statistics and curbs potential coercions from the domain expert to provide a rushed statistical solution. Rather than feeling "put on the spot," students can consult their books, peers, faculty members, and other resources to devise their $Q_2$ approach after the initial meeting has concluded. This empowers students to find a proper solution, not just an expedient one. As Banks stated in his 2023 ASA Deming Lecture, “At this level of detail [of current problems in industrial statistics], there are no general theorems. Every application requires a bespoke solution. And that requires someone with statistical training to sit with domain experts to figure out the particularities of a problem.” (2023,p. 19)

Fourth, we believe that emphasizing the evidence to “action” part of $Q_3$ will lead statisticians and data scientists to have greater impact on their projects. In our personal experience, statisticians in academia are rarely involved in the “action” resulting from their modeling and analyses. As a result, the full value of the analyses are not realized for most collaborative projects. How to inculcate an evidence-to-action mindset in our students is a topic of discussion in the next subsection.

## 6.4 Future Work and Limitations

How to instill a mindset of “evidence into action” in statistics and data science students remains unsolved and is the subject of ongoing work. We hope that this paper will inspire more statistics and data science educators to think about how to do this and experiment with innovative methods. We believe that the principles of “evidence communication” in Blastland et al. (2020), which advocate for a clear separation between information and opinion and encourage researchers to adopt a reflexive stance about their intentions to inform or persuade, will be valuable tools for statisticians and data scientists who want their work to achieve greater impact for societal good.

One of the limitations of our study of the efficacy of our methods for teaching the $Q_1Q_2Q_3$ workflow is that it relied on students’ self-reflection rather than an objective evaluation of students’ $Q_1Q_2Q_3$ skills. Future work may include designing objective evaluations and investigating the usefulness of $Q_1Q_2Q_3$ at independent validation sites outside of the authors’ home institutions with a variety of instructors.

Finally, we believe that the $Q_1Q_2Q_3$ workflow is a useful advancement toward developing a theory of applied statistics, which was called for by Mallows (1998). We hope that others can expand upon $Q_1Q_2Q_3$ in ways to make applied statistics and data science easier to teach and statistics and data science easier to correctly apply.

## 6.5 Recommendations

### 6.5.1 Teach $Q_1Q_2Q_3$ in an introductory course

We echo call from statistics and data science educators to incorporate qualitative thinking in the first-year course and throughout the statistics major curriculum (Horton 2016). Before they learn methods, students should learn that the context of the problem and the provenance of the data informs which methods are most appropriate to use.

We recommend teaching the $Q_1Q_2Q_3$ workflow at the beginning of statistics and data science introductory courses. Doing so can create the opportunity later in the course to introduce qualitative methods useful for improving the learning and application of statistics (Gal and Ograjenšek 2010). Even without focusing teaching on any qualitative methods, introducing $Q_1Q_2Q_3$ early in the course will help students recognize that the reason $Q_2$ methods are applied (i.e., why students are even learning the methods in the first place) is to compile quantitative evidence for $Q_1$ questions to produce relevant $Q_3$ answers.

Educators can teach $Q_1Q_2Q_3$ in introductory courses by asking students to read a summary of $Q_1Q_2Q_3$ (see for example https://osf.io/z6wdg/) or briefly lecturing about it, and then referring to the qualitative ($Q_1$), quantitative ($Q_2$), and qualitative ($Q_3$) aspects of any statistics or data science problem addressed in class. $Q_1Q_2Q_3$ can also be used a template or outline for students' class project reports (e.g., a report with three sections: What is the problem? [$Q_1$], What did you do? [$Q_2$], and What does it mean? [$Q_3$])

### 6.5.2 Teach $Q_1Q_2Q_3$ in a capstone or collaboration course

We believe that making students explicitly aware of all of the important work that comes before and after a statistics or data science analysis is essential for any course in which students conduct projects, including capstone courses and consulting or collaboration courses. In such courses, we recommend sampling liberally from the content and exercises described in Section 4. At a minimum, follow the recommendation for introductory courses and provide students the opportunity to read about $Q_1Q_2Q_3$ and then talk about this workflow throughout the course. We recommend educators assimilate $Q_1Q_2Q_3$ into their pedagogy and make it become part of their in-class vocabulary.

Also, for collaboration courses or capstone courses in which the students will meet with domain experts, teach the POWER structure (Prepare-Open-Work-End-Reflect) for meetings (Alzen et al.

2024; Zahn 2019) and explicitly differentiate for students how the $Q_1Q_2Q_3$ workflow is for *projects* and the POWER structure is for *individual meetings*.

### 6.5.3 Encourage collaboration in all statistics and data science projects

A data scientist should never work alone because statistics and data science are team sports. In our experience, class projects (including Kaggle-style contests) in which a student (or a team of students) finds an "interesting" dataset; develops their own research questions; conducts analyses; and communicates their findings, conclusions, and recommendations have all of the components of a real project, yet fall short on their desired impact on students' learning and society at large. These projects can be used to exhibit students' technical skills, but too often the research questions and final results are ultimately meaningless.

Instead, educators can encourage genuine collaborations, where a domain expert originates the problem; answers the collaborative statisticians' and data scientists' questions about the $Q_1$ context and the $Q_3$ relevance, recommendations, and plans for action; and is in a better position than a statistics or data science student to use the project's results for societal good.

# 7. Conclusion

Every statistics or data science project or investigation must mix qualitative and quantitative thinking. This paper describes the $Q_1Q_2Q_3$ workflow for the content of statistics and data science collaborations, explicitly emphasizing the importance of the qualitative context of a project at its beginning ($Q_1$) and the qualitative interpretation ($Q_3$) of quantitative findings ($Q_2$) near its end. In our experience, statisticians and data scientists readily understand quantitative thinking, and most need to exercise their qualitative thinking. $Q_1Q_2Q_3$ helps to do that.

We provided guidance for students and practitioners to implement the $Q_1Q_2Q_3$ workflow and strategies for teaching it. We also presented data demonstrating the effectiveness of teaching $Q_1Q_2Q_3$ to beginning collaborators. Teaching this simple yet versatile workflow provides value in the classroom and on collaborative projects. We recommend that $Q_1Q_2Q_3$ be taught early in introductory statistics and data science courses and again in capstone or collaboration courses. $Q_1Q_2Q_3$ can be considered as part of a foundation for a theory of applied statistics that provides statisticians and data scientists with a framework for successfully contributing to research, policy, and business decisions and transforming evidence into action for the benefit of society.

# Acknowledgements

This material is based upon work supported by the National Science Foundation under Grant No. 1955109, Grant No. 2022138, and Grant No. 2044384 for the projects, “IGE: Transforming the Education and Training of Interdisciplinary Data Scientists (TETRDIS)”, “NRT-HDR: Integrated Data Science (Int dS): Teams for Advancing Bioscience Discovery”, and “CODE:SWITCH: Integrating Content and Skills from the Humanities.” This work was also partially supported by the United States Agency for International Development under Cooperative Agreement #7200AA18CA00022. We would like to thank the Laboratory for Interdisciplinary Statistical Analysis (LISA) student collaborators and domain experts, as well as students from the Statistical Collaboration course at the University of Colorado Boulder.

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