A Framework for Successful Statistical Consulting: A Concise, Field-specific Handbook to Help the Scientist Make Effective Use of Statistical Methods in Their Field

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Abstract
Inherent to statistical consulting and collaborations across disciplines is the need to balance the quality of statistical argumentation with the specific expectations and standards of the investigator's field. In this paper, we present a framework we developed to facilitate a successful collaboration with researchers in the field of dental material science—by improving communication about the scientific context of the research question and the statistical methods employed. Drawing on our experiences from this collaboration, we describe techniques for how to bridge the complexity of statistical methodologies with the scientist who may be unfamiliar with these tools. In particular, we underscore the value of producing a concise handbook for the statistical methods and analysis specific to the research questions emerging in the investigator's field. The handbook was created after a survey of papers in the field of dental materials, and provides accessible explanations, field-specific examples and accompanying applets for the principal statistical tools we encountered in this research area.

Key Words: consulting, communication, scaffolding, statistical handbook, dentistry

1. Introduction

Statistical consulting is an inherently collaborative endeavor that brings together the expertise of the statistician and that of the client to answer specific questions requiring the use of statistical methodologies. Since the collaboration involves communication at several stages of the project—such as understanding and refining of the research question, designing of appropriate experiments to collect data, the analysis of the data, as well as the interpretation of the result, the quality of the collaboration depends strongly on the implementation of "essential collaboration skills" (Vance and Smith 2019, p.1). Derr (2000) highlights the need for the statistical consultant to "master skills in communication that promote effectiveness in statistical consulting" (p.2), which can lead to a positive experience for both the client and the statistician.

While the statistical expertise of the consultant is essential, the effectiveness of the collaboration depends strongly on the interpersonal skills and the ability of the statistician to involve the client in the analysis (Boen 1982). A multitude of authors highlight the necessary communication skills to be an effective statistical consultant and offer frameworks for developing and employing these skills (Hand and Everitt 2007, Cabrerra and Dougall 2002, Derr 2000, Vance and Smith 2019). In fact, the American Statistical

Association outlines the importance of incorporating the teaching of collaboration skills as part of the statistical undergraduate program (ASA 2014), in order to ensure that the practicing statistician is able to communicate statistical ideas and work well as part of a team.

A key component for a successful collaboration is the ability of the statistician and the client to effectively communicate ideas using terminology from their own fields. Hand (2007) describes the ideal consultation as “a working-together” (p.1), and highlights the importance for both sides to be familiar with each other’s basic disciplinary language. Both the lack of statistical knowledge on the part of the client, and the lack of familiarity of the consultant with the basic terminology in the client’s discipline, can be sources of potential pitfalls for the collaboration, as they can give rise to fundamental misconceptions and difficulties. Kimball (1957) also identifies that at times the fault for miscommunication around the scientific context of the project can reside with the statistician’s lack of sufficient familiarity with the problem in order to be able to offer “advice intelligently” (p.135). As a result, errors in consulting can appear because of the inadequate communication between statistician and researcher. To ensure a productive collaboration and overcome such errors, the statistical consultant should seek to develop a basic familiarity of the client’s discipline by conducting a brief survey of the available literature related to the research topic for the project.

However, the statistician must also help the client overcome the complexity of the various statistical methodologies employed in the project. Hand (2007) identifies that one of the important roles that the statistical consultant plays in the collaboration is to educate the client in the statistical methods used during the collaboration. The lack of understanding of statistical methodologies for the client can often constitute a significant barrier of communication. Martin (2003) recommends the use of analogies as an important pedagogical approach for teaching introductory statistics, which can also be extended to the setting of statistical consulting where the statistician introduces the client to different statistical methodologies and tools for their project. According to Martin (2003), “analogies are designed to demystify statistical ideas” (p.1) by placing them in a context familiar to the researcher. By appealing to the researcher’s disciplinary experience, common misconception about statistical methodologies and ideas can be avoided. The familiar context to the researcher can help the client bridge the complexity of the statistical methods and better understand how these tools apply to their specific scientific context.

Barriers of communication between the statistician and the client can exist due to lack of disciplinary knowledge of the statistician about the research question, as well as the lack of understanding of the statistical methodologies in the case of the client. In the following sections we describe a framework we developed for long-term collaborations in the academic setting that addresses both of these barriers of communication. To help the statistical consultant familiarize themself with the researcher’s field, we recommend surveying research papers on the topic of investigation, which can provide the statistician with both a basic understanding of the terminology and research question, as well as of the field-specific standards for the statistical analysis. This survey can also be the basis for developing a concise handbook outlining the principal statistical methodologies that can serve as a foundation for communicating statistical ideas to the researcher. By using analogies and examples derived from the researcher’s own field, the statistician can help communicate statistical ideas through this handbook in a familiar setting to the researcher. Vance and Smith (2019) also highlight that diagrams can be effective tools for conveying statistical ideas, and so the use of flowcharts as part of such a handbook is recommended.

The goal of this article is to outline the framework established to facilitate successful long-term collaborations with academic researchers (see section 2), and to describe the different elements encompassing such a field-specific statistical consulting handbook (see section 3) developed in support of this collaboration.

2. Collaboration Framework

Inherent to statistical consulting is the interdisciplinary collaboration between the statistician and the investigator and the challenges that arise both from the nature of the research project and the interpersonal communication and dynamics on the team. In the following we describe a framework we developed to facilitate a successful collaboration with academic researchers in the field of dental material science by improving the communication between the statistician and the researcher, and developing a field-specific handbook to be used as scaffolding for navigating the statistical methodologies employed in the collaboration. While the handbook presented in section 3 is specific to the field of dentistry, the components of this framework can be applied broadly across different disciplines.

An essential component to any collaboration between the statistician and the disciplinary researcher is the need to learn from each other, given that the statistician does not have knowledge about the scientific context for the research question, and the investigator is often unfamiliar with the complexities and limitations of statistical methodologies. A collaboration that is most productive emerges when both the statistician and the researcher are part of stimulating meetings where both sides can learn from each other. The statistical consultant must play an important role in helping the researcher learn about statistical methodology and its uses, while the statistician needs to understand the scientific context in order to properly assist in hypothesis formulation, experimental design, and data analysis. This includes learning the terminology and other relevant aspects from the investigator's research field. In order to deepen the collaboration and the results of the analysis, the statistical consultant may find it useful to read several research papers related to the topic under investigation in order to get a better understanding of the current research status and the field-specific standards for the analysis. Another important aspect inherent to statistical consulting and collaborations across disciplines is the need to balance the quality of statistical argumentation with the specific expectations and standards in the investigator's field. While statisticians may be inclined to recommend the use of certain statistical methods for the analysis, it is useful to also consider the standards used in publications in the researcher's field.

A successful consulting experience also requires an overall structure for the collaboration, which of course starts by jointly identifying the specific goals for the project. A good strategy for accomplishing a productive collaboration is to clearly define the goals and delineate the responsibilities and expectations for the collaboration, including a discussion about authorship of potential research papers. Joint authorship can be a demonstration that both sides value each other's expertise, and may incentivize the statistician to a greater time commitment for the project leading to a better, deeper statistical investigation. The statistician and researcher can thus take the time to consider the problem, refine the analysis, learn from each other and discuss the results and their implications at several meetings. A meaningful collaboration, which will result in a long-term partnership, is based on the shared understanding of each other's strengths and a recognition that both the investigator and the statistician bring invaluable expertise to the project that is recognized through joint authorship.

While it is important to define goals right at the beginning of the collaboration, these must be understood as being organic, as they will evolve and be refined throughout the duration of the project. The same is true for having a structure for the meetings between the investigator and the statistician. It is certainly important for both sides to come prepared to the meetings with specific questions, summaries of the joint understanding of the progress made to date, project reports for the data collection process, statistical analysis and interpretation of results, as well as plans for the next steps with timely deadlines. However, it is also essential to engage in a continuous dialogue with the investigator and adapt these plans to a newly gained understanding from the meeting. For example, the statistician may recommend a certain experimental design with a specified number of specimens that should be generated from the data collection process. They may however learn from the investigator that in their field, the preparation of sample specimens can take months or longer and be very cost-prohibitive, and so the statistician may need to adapt the initial recommendations to reflect this new understanding. By engaging in a dialogue early on with the investigator, the statistical consultant can gain a better understanding of the limitations imposed by the specific research field. The same holds true for involving the researcher at every step of the statistical investigation, so they can be presented with different options for the analysis or display of results, as well as be able to contribute their scientific expertise to a refined analysis. These frequent interactions between statistician and investigator can prompt new questions and perhaps a new direction in the investigation, which can consolidate a long-term collaboration.

The investigator generally seeks out the statistical consultant during two stages of their research project—after having identified some research questions they seek to answer, or alternatively, after the collection of data for the experiment is completed. If the collaboration starts early in the design phase of the research project, the statistician can help translate the investigator’s research questions into specific statistical hypotheses and produce an experimental design that will lead to data that address the specific research questions. However, if the investigator has already completed the experiment and is only looking for assistance from the statistician with the data analysis, they may find that the data collected is inadequate for the initial research question for their project. Overcoming experimental designs that are inadequate for the research question is often difficult and requires collection of additional data, which can create a stressful situation for the investigator. Hence a crucial component of a successful collaboration is the need for thoughtful communication in dealing with setbacks in the research project. It is important for the statistician to not only highlight the inadequacy of the data for the proposed research question, but to also offer some constructive alternatives to the investigator, who may otherwise feel disheartened. These choices for how to communicate setbacks can ensure a positive experience for both the statistician and the researcher that can lead to long-term collaborations and joint papers.

Communication is also essential in the last stages of the collaboration, when the investigator may be presented with software output and a brief outline of the results for the statistical analysis that they then need to interpret in their specific scientific context in their research paper. The investigator may feel overwhelmed by the statistical terminology and have difficulty translating the results presented by the statistician in terms of their initial research questions. It is therefore important that the statistical consultant also take part in the interpretation of the software output and results of the analysis, and be available to answer questions from the investigator. The discussion aspects of a research paper are perhaps the most significant part of the journal article, and the statistician should continue to be an important resource at this stage. These conversations at the final stages of the project can again lead to a refined analysis and strengthen the collaboration by giving rise to new questions for a future research project.

However, one of the most common barriers to a successful collaboration is the challenge for the investigator to overcome the complexity of the various statistical methodologies. The typical researcher has some familiarity with introductory statistical terminology and methods, however they may not understand the underlying assumptions for these statistical methods nor be able to delineate the appropriate settings for employing these tools. During our own collaborations we identified the need to reduce the complexity of the statistical methodologies for the researcher to the types of questions typically emerging in the investigator's field. This may be particularly relevant if there are multiple investigators on the team that have different levels of expertise and interest in the statistical analysis, which the consultant must attempt to balance.

The statistician looking for long-term collaborations may therefore find it useful to develop a concise, field-specific statistical handbook that can provide the researcher(s) with a scaffolding for learning the basic ideas for the statistical methodologies used for the project. The handbook should also provide decision trees to help the researcher understand how the setting for their particular research question fits into the multitude of available statistical tools. Having field-specific explanations and examples in the handbook can often be the key to overcoming the technical difficulties in understanding the uses and limitations of the various statistical methods. In the following section, we provide a description of the different components of the statistical handbook we developed for the field of dentistry in support of our collaboration with researchers in this discipline. It has been our experience that the use of such a handbook in the collaboration does not diminish the role the statistician plays in the partnership, as they will still play a major part in all aspects of the project, including overcoming difficulties in the analysis—such as problems with data or missing values and violating assumptions of statistical methods. This will however enable the statistician to more easily overcome the communication barriers around statistical methodologies and thus elevate the analysis to a higher level.

3. Statistical Handbook

3.1 Overall Approach

For statistical consulting and collaborations across disciplines, the need arises to reduce the complexity of statistical methodologies for the researcher to the types of questions typically emerging in the investigator's field. Given that the investigator may not be an expert in statistics, they can easily become overwhelmed by the statistical terminology and the multitude of choices before them for the statistical analysis. To help the researcher navigate these choices as well as the intricacies of the various statistical methods, the statistician can develop a concise, field-specific handbook that provides an introduction to the principal statistical tools and methodologies commonly used in the researcher's field. In the following, we outline elements of such a field-specific handbook we developed for the field of dentistry as part of a long-term collaboration with academic researchers in the area of dental materials. The handbook was developed after a survey of papers in this research area to identify the specific expectations and standards of the investigator's field. The handbook attempts to strike a balance between quality of the statistical argumentation and the field-specific expectations and standards observed through this survey of papers.

Our statistical handbook developed for the field of dentistry includes accessible explanations for the dentistry researcher, field-specific examples, practical advice, flowcharts for deciding which statistical methodologies to employ, explanations for underlying assumptions and how to check them, as well as accompanying R-code for the principal statistical tools. The goal of the handbook is to provide a concise compendium of the primary techniques used in the research area of dentistry while ensuring the ease of use for the researcher. To keep the handbook brief, the authors made several choices as to the information included and the technical details highlighted for each statistical methodology. Given that the typical researcher does not have the necessary time to consult the extensive literature on statistical methodologies, brevity was an important feature of this handbook. The following subsections offer a brief outline of the various elements included in this handbook and include some excerpts as examples; the full version can be found on the website dentalstathandbook.com.

3.2 Hypothesis Testing and Assumptions

The handbook begins by introducing the reader to the basic ideas and terminology of hypothesis testing. A common point of confusion among beginning users of statistics is the reason why the research claim must be formulated as the alternative hypothesis, and thus the hypothesis testing procedure is one through which the value of a test statistic will be used by the researcher as evidence against the null hypothesis. To help the investigator understand this underlying idea about hypothesis testing, the handbook offers an analogy about subjecting scientific claims to rigorous testing in order to convince a skeptic to adopt the researcher's claim, and thus is able to frame this difficult concept in a scientific context that the researcher is familiar with (see excerpt below). By using analogies and contexts familiar to the investigator throughout the handbook, we are able to ensure that the ideas and methodologies outlined are accessible to the researcher.

> Subjecting scientific claims to rigorous testing ensures a high standard for adopting new claims. When a researcher makes a claim about a population or a process, that claim is subjected to an empirical test so as to convince a skeptic, who requires strong evidence, to accept this new claim. The test therefore proceeds as if to convince a scientific skeptic to agree with the researcher's claim. The scientific skeptic begins by nullifying or refuting the researcher's hypothesis, thereby assuming that the null hypothesis holds. An experiment is designed through which data is collected and a test statistic is produced that will be used for the purpose of persuading the skeptic to change their mind. The researcher will use the value of the test statistic against the skeptic's null hypothesis. If the value of this test statistic is sufficiently implausible to the position of the skeptic, who is assuming the null hypothesis is true, they will decide to not reject the researcher's claim—the alternative hypothesis.

Since each statistical methodology has underlying assumptions that must be satisfied before the technique can be employed, the handbook also offers a brief introduction to the topics of normality, independence and constant variance. The explanations for these assumptions are accompanied by field-specific examples and offer accessible tools for assessing if the assumptions are satisfied. In the case of normality, the handbook introduces graphical methods and the Ryan-Joiner test with specific criteria for assessing fit of data to a normal distribution.

Since preparing samples for experiments in the field of dentistry can be very time consuming as well as expensive, it is often the case that experimental settings in dental research papers have small sample sizes. Given this field-specific characteristic for the size of samples in dentistry, we included in the handbook several examples of normal probability plots generated from normal distributions (see figure 1 below) to demonstrate the variability present in these plots when the sample size is small. By offering these examples of normal probability plots showing deviations from the linear pattern that are not pronounced, we can educate the reader that for small samples only strong patterns should be taken as evidence against normality, and thus address a common question that arises in this field.

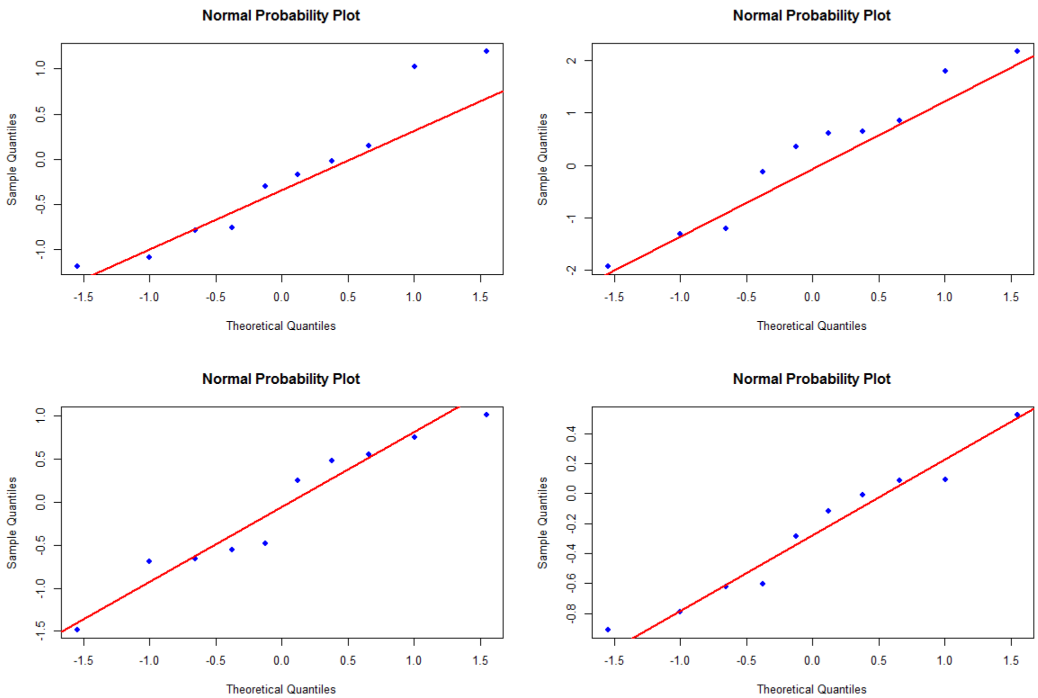


Figure 1: Normal Probability Plots for Small Samples Generated from Normal Distributions

The handbook also offers practical advice for when an assumption is not satisfied and discusses the different choices before the researcher. For example, while some statistical methods can be employed in the absence of normality when the sample size is large ($n \geq 30$), collecting data on an experiment with 30 specimens instead of say 12 specimens can be prohibitively expensive in dentistry. Hence, the researcher can instead consider using non-parametric methods, in which the underlying distribution of the population does not need to be known, or to transform the data to correct the deficiencies. However, as part of the dialogue with the researcher during the collaboration, the statistician can explain the tradeoff for using non–parametric versus parametric techniques—that by making fewer assumptions about the population distribution when using non-parametric techniques, these tests are less powerful than their parametric counterparts when the normality or large sample size assumptions hold.

3.3 Flowcharts

To help the dentistry researcher overcome the multitude and complexity of statistical methodologies, the handbook provides the reader with several flowcharts that can guide the investigator in identifying correct approaches for the specific settings of their investigations. Figure 2 below shows the flowchart for the one-factor analysis when normality or large sample size is present. The diagram helps the researcher identify the appropriate statistical methodology based on simple queries about assumptions and number of groups. Once the researcher has recognized the specific methodology for their research setting, they can then access the section of the handbook that introduces the specific methodology and provides guidance for how to employ the technique.

However, navigating these flowcharts that utilize specific statistical terminology can be confusing to the researcher, and so the handbook also contains accessible explanations of how to make choices between the different techniques in the flowchart—such as between one, two or more groups as well as between parametric and non-parametric tests. These explanations are accompanied by field-specific examples that can help the researcher better understand the context of the query when making choices in the flowchart for their research question (see excerpt below).

Distinguishing between One, Two or More Groups: The one-group methods apply to settings where the research question is about a single population. On the other hand, if the researcher is interested in comparing two populations, then methods from the two-group setting should be applied.
For example, suppose the goal of the researcher is to understand the effect of irradiation on the flexural strength of a composite dental material. If the question is to determine whether irradiation affects the strength of a particular composite material or estimate this effect, then a one-group method should be applied. If on the other hand, the researcher is interested in comparing the effects of irradiation on two different composite materials, then the two-group setting methods should be used, and to compare 3 or more composite materials, the One-way ANOVA should be used.
A two-group setting also arises when the goal of the researcher is to compare the effect of 20 days of exposure to irradiation to that of 40 days on the same composite material. Here Group 1 consists of the composite specimens exposed for 20 days and Group 2 of the specimens exposed for 40 days. If the measuring process does not destroy the specimens, then it is possible that the same specimens are measured at day 20 and at day 40. So even though they are the same physical specimens, they form different treatment groups. In this setting, a paired comparison test can be used.

Moreover, given that the researcher might feel disoriented by the many available choices in the flowchart, the handbook also offers recommended paths, which are highlighted in the flowchart to draw attention to the statistical methodologies most commonly used. For example, we highlight in red the recommended path when choosing between a z- and a t-test. Given that in the typical research scenario, the value of the population standard deviation σ is unknown, and so it must be estimated, we recommend the use of the t-test instead of the z-test to assess the plausibility of the underlying research hypothesis.

The handbook also contains flowcharts on the one-factor analysis of variance, simple linear regression and non-parametric methodologies (see figures 2 and 3 below). The diagram for ANOVA distinguishes between single and multiple comparison methods and introduces Tukey, Bonferroni and Scheffé's methods as the most commonly encountered methodologies for multiple comparison methods in the field of dentistry. The flowchart for simple linear regression highlights the different choices available for the regression analysis, while the diagram for non-parametric tests offers a decision tree for the most frequent non-parametric techniques encountered in dentistry.

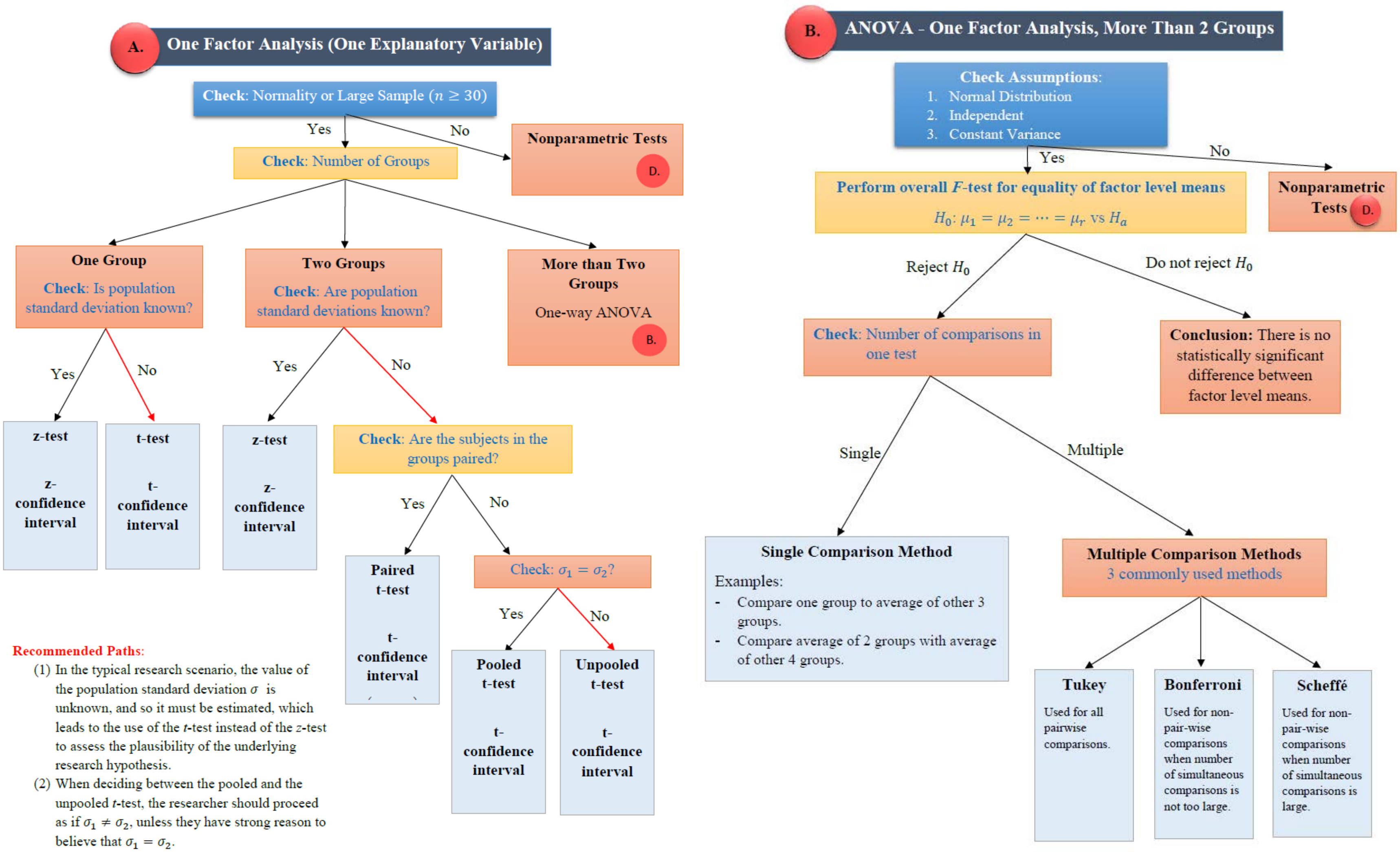


Figure 2: Flowcharts for One Factor Analysis and ANOVA

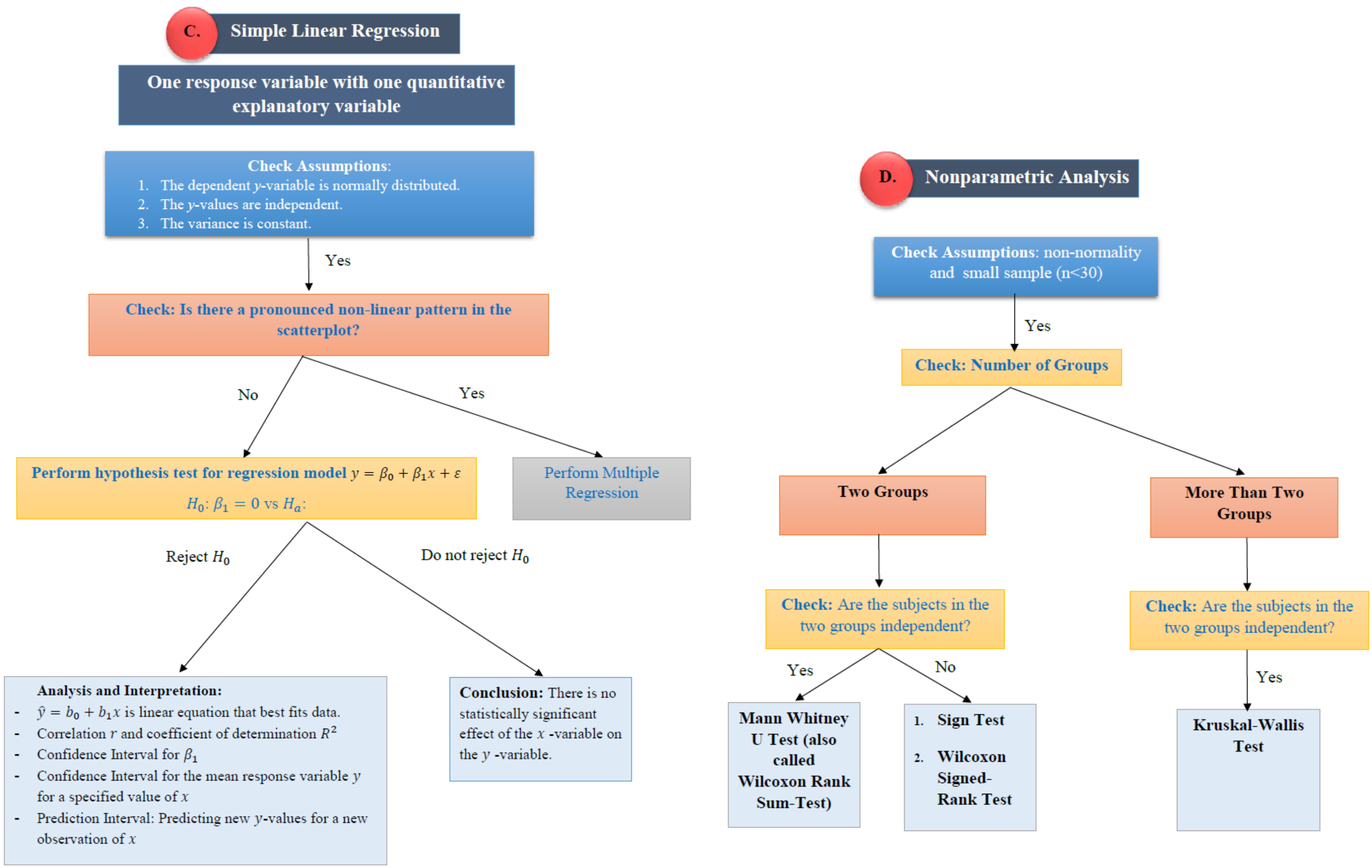
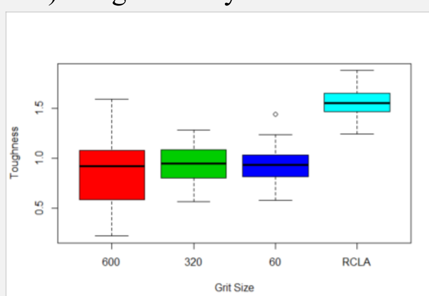


Figure 3: Flowcharts for Simple Linear Regression and Non-Parametric Tests

3.4. Field-Specific Examples

To overcome the abstractness of the process for each statistical methodology as well as help the researcher better understand its uses, the handbook contains multiple field-specific examples for each statistical methodology that were drawn or adapted from the survey of 35 papers in the field of dental materials. For each example, we briefly introduce the specific setting of the research question, verify the assumptions for the methodology employed, as well as offer a summary of the software output and an analysis of the results. By offering a detailed interpretation of the output of the R-code and drawing conclusions just as the investigator would in a research paper, we enable the dental researcher to reproduce the same language for the analysis in their project. For instance, the excerpt below highlights the use of Scheffé's method to conduct a post-hoc analysis of population means to determine the strength of adherence between different resin composites.

Comparing Strength of Adherence: To investigate if the strength of the adherence between a resin composite block and the luting agent (RCLA) depends on the surface roughness of the block, a researcher prepares 80 specimens by subjecting each group of 20 to no sanding (RCLA), as well as sanding using 600, 320, and 60 grit SiC papers, respectively. The interfacial fracture toughness is measured for each of the 80 specimens. The researcher performs the ANOVA overall F-test ($p \leq .05$) and rejects the null hypothesis that the four population means are equal. The researcher then visually inspects the boxplot and decides to do a post-hoc analysis to assess if the mean μ_4 for group 4 (RCLA) is significantly different from the other 3 means.



Since this is a post-hoc analysis the researcher should use Scheffé's method. The following five contrasts are set up for a simultaneous hypothesis test at level α=.05:

c_1	c_2	c_3	c_4	Comparison
-1	0	0	1	Compares μ_4 with μ_1
0	-1	0	1	Compares μ_4 with μ_2
0	0	-1	1	Compares μ_4 with μ_3
$-1/3$	$-1/3$	$-1/3$	1	Compares μ_4 with average of μ_1, μ_2 and μ_3
$-1/4$	$-1/4$	$-1/4$	$3/4$	Compares μ_4 with average of μ_1, μ_2, μ_3 and μ_4

The software output below indicates that all five contrasts are significantly different from 0, since the individual p-values are less than 0.05. With 95% confidence, the researcher concludes that μ_4 is larger than the other 3 means as well as their average.

Contrast	Difference	Lower CI	Upper CI	Adj p-Value
L_1	0.6243813	0.5798700	0.6688926	2.177141e-10
L_2	0.6246019	0.5800906	0.6691132	2.149894e-10
L_3	0.6975321	0.6530208	0.7420434	3.312017e-12
L_4	0.6488384	0.6124951	0.6851818	1.332268e-14
L_5	0.4866288	0.4593713	0.5138863	1.332268e-14

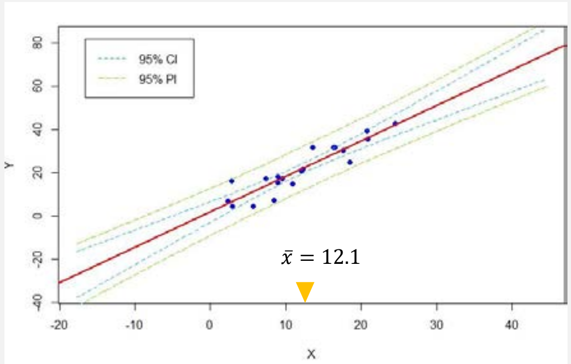
Another important aspect of the handbook is the use for pedagogical reasons of the same underlying contexts for examples of different statistical methodologies produced by varying the setting and assumptions for the underlying data. For instance, the same context of irradiating 30 specimens of composite dental material(s) for 40 days to study its effects on the strength of the material is used for (1) the one-group t-test with only one composite material, (2) the pooled t-test when comparing two composite materials from two companies with the same production standards, and (3) the unpooled t-test when after conducting an F-test it is determined that the assumption of equal variance is violated. By using the same general idea for the experimental setting, but varying the number of groups and the assumption of constant variance in these examples, the investigator is able to gain a better understanding of how the choice of statistical methodology depends on the details of each of these different settings.

Irradiation Effects on Flexural Strength: 30 specimens of a composite dental material are subjected to ionizing radiation used in the treatment of cancer patients for 40 days. Flexural strength of the material is measured for each of the 30 specimens after irradiation. One research goal is to estimate the mean flexural strength after irradiation and determine if it exceeds a minimally acceptable threshold for flexural strength μ_0 of composite materials used in dental restorations. The researcher is concerned the composite material is weakened as a result of irradiation. Wanting to guard against using composite materials that would become unacceptably weak after irradiation such as that experienced by cancer patients, we choose the null hypothesis to be H_0: $\mu < \mu_0$. Since the sample size n=30, the researcher can use the t-test and obtains a p-value of 0.00172. Since the p-value is less than the significance level α = 0.05, the researcher rejects the null hypothesis and concludes that the composite material has the required minimal flexural strength after irradiation. The example is continued in section II.3, when the researcher is interested in comparing the flexural strength after irradiation of materials from two different companies, in which a pooled t-test for two groups will be employed.

3.5 Practical Advice

Another helpful tool to assist the dental researcher in navigating the handbook in support of the statistical analysis for their investigation is the specific practical advice offered for employing each statistical methodology. These practical advice components offer a way to address in a succinct manner common questions about a certain statistical tool as well as offer important information about its uses and limitations. For example, the excerpt included below of the practical advice for some uses of simple linear regression draws the distinction between confidence and prediction intervals, and offers a visual representation of the changes in the width of these intervals as a result of an increase in uncertainty as the values move further away from the sample mean.

Prediction intervals and confidence intervals differ conceptually. A confidence interval is used to estimate the value of a population parameter such as a mean, whereas a prediction interval is used to estimate the value of the response variable on a new trial performed independently of the data used to produce the regression model. The confidence interval for the mean response at each given value of x has a margin of error that is smaller than the corresponding prediction interval for estimating a single new y-value.



The margin of error for a confidence or prediction interval grows larger as the specified x-value x_h gets further from the sample mean $\bar{x}$. This accounts for the increasing uncertainty in attempts to extrapolate beyond observed data points; however, the researcher should still be cautious in any attempt to apply the model to values of x beyond those that have been included in one's study because there is no guarantee that the linear trend will continue.

The practical advice components in the handbook also address some common misconceptions identified in the survey of dental papers in the field of dental materials, as well as offers suggestions for how to improve the analysis. For example, the practical advice included below explains that reporting observed values using the mean and standard deviation ($\hat{\mu} \pm SD$) is no substitute for confidence intervals, and in particular for 95%-simultaneous confidence intervals for multiple groups as produced by Tukey's method.

In practice, some research papers report the results of experiments using the mean and standard deviation for each group and summarize the observed values as $\hat{\mu} \pm SD$. For example, a researcher may report the wear for dental materials for 3 groups as $65 \pm 4\ \mu m$ for group 1, $255 \pm 13\ \mu m$ for group 2, and $257 \pm 24\ \mu m$ for group 3. If the populations are normally distributed, then the intervals reported above (one standard deviation from the mean) are 68% confidence intervals for each individual group, and so overall the simultaneous confidence in this list of intervals is substantially decreased. The Tukey confidence intervals on the other hand offer simultaneous 95% confidence intervals, so the researcher can with at least 95% confidence produce interval estimates of all pairwise differences $\mu_i - \mu_j$ simultaneously.

3.6 R-Code

The handbook is accompanied by code for the language R for the principal statistical techniques outlined in the compendium. To make the programming aspect of the research project more accessible to the researcher, the handbook contains R-code that can easily be used by the researcher for their project by simply replacing the data in the example with their own. To accomplish this, the handbook provides three accessible methods for the researcher to load their data intro RStudio that are introduced in short videos. Since Excel spreadsheets are commonly used to store experimental data, the videos highlight three easy ways in which the researcher can import data from Excel into RStudio. Given that the typical researcher does not have extensive experience with R, this strategy ensures that the programming aspects of the research collaboration are also accessible to a certain degree to the investigator, so they can use the R-code to perform some preliminary exploration of the data or to customize graphs to their specifications.

Visualizing Scatterplot for Regression: R script file

```
###----------------------
### create scatterplots
###----------------------

#1# store data

    xdata<-c(73.24,
             73.22,
             74.39,
             73.28,
             73.75,
             75.26,
             76.46,
             74.35,
             74.46,
             76.51,
             77.3,
             77.31,
             74.61,
             77.41,
             78.21,
             78.08,
             78.38,
             75.13,
             76.74,
             78.86,
             79.21
    )
    ydata<-c(20.0000,
             18.9167,
             21.0833,
             45.1667,
             50.0833,
             39.5833,
             97.1667,
             101.1667,
             96.6667,
             153.3333,
             151.1667,
             148.6667,
             199.3333,
             200.8333,
             200.5833,
             266.4167,
             258.1667,
             261.5833,
             298.6667,
             304.8333,
             299.1667
    )

#2# graph points

    #example 1 with basic graphing functionality
    plot(xdata,ydata)

    #add regression line
    abline(lm(ydata~xdata))

    #example 2 with more graphing options
    plot(x=xdata,
         y=ydata,
         pch=21,#plotting character is circle
         bg="blue",#fill color of circle
         col="blue",#boundary color of circle
         cex=.75, #75% of normal circle size
         xlab="Xlabel",
         ylab="Ylabel",
         main="Title",
         cex.main=2, #200% of normal title size
         cex.lab=1.25 #125% of normal axes label size
    )

    abline(lm(ydata~xdata),
           col="red", #line color
           lwd=1.5 #150% of normal line width
    )
```

Figure 4: Example of R-Code with Several Options

4. Conclusions

A successful statistical consulting experience requires that both the statistician and the researcher take part in a stimulating collaboration, in which both sides can learn from each other. While the researcher is benefitted by the expert statistical knowledge of the consultant, the statistician may also find it useful to read multiple research papers in the investigator's field to better understand the scientific context of the researcher's questions. Problems facing the statistical consultant can vary from poor design of experiment, issues related to data such as missing values, and interpersonal challenges when working with the researchers. There are many potential setbacks in a collaboration but they can successfully be overcome through good communication, a structured approach to the meetings, and starting the collaboration early prior to the design of the experiment. The statistician should impress on the researcher the need for the collaboration to start at the early design stages of the project in order to avoid setbacks. By starting with the general research questions of the investigator, the statistician can work with the researcher to understand the experimental setting, formulate appropriate statistical hypotheses, and help them design an appropriate experiment to address their research questions. This must be done in partnership, as the statistician may not be aware of limitations around the experiment—such as the cumbersome preparation of specimens that may take months to process and thus limit the sample size.

To overcome the complexity of statistical methodologies, and encourage long-term collaboration, the statistician can develop a concise statistical handbook with field-specific examples that can help the researcher understand the uses of these methods in familiar scientific contexts. By incorporating practical advice about the uses and limitations of statistical tools as well as flowcharts that help the researcher navigate the many choices in conducting a statistical analysis, the statistical consultant can provide the researcher with scaffolding that aids them in learning the fundamentals of the statistical methodologies employed in the project. Equally important is the willingness on the part of the statistician to delve into the research field for the study in order to understand the scientific context for the statistical investigation, which along with good communication skills for navigating setbacks in the project, can lead to a successful long-term collaboration.

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