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1 Statistics and Models

"Why do I need to take statistics?"

Every semester that I teach statistics I have students asking this question. It's a fair question to ask. Most of my students want to work as therapists, social workers, psychologists, anthropologists, sociologists, teachers, or in other jobs that seem far removed from formulas and numbers. As students majoring in the social sciences, almost all of them are more interested in people than they are in numbers. For many students (including me, a long time ago), statistics is something to get out of the way so that they can devote their attention to the stuff they *really* want to do (Rajecki et al., 2005).

The purpose of this chapter is to show you why students majoring in the social sciences have to take statistics. This chapter will also explore some introductory concepts and terminology that are necessary to understand the book. The most important idea introduced in this chapter is the concept of models, which many experts use to understand their statistical results. Because my goal is to help you think about statistics like a professional, I will use that perspective throughout the book.

Learning Goals

After studying this chapter you should be able to:

- Explain why students in the behavioral sciences need statistics to be successful in their majors.
- Outline the general process for designing and executing a research study.
- Describe the benefits of using models to understand reality.
- Demonstrate why using a model – even if it is not completely accurate – is useful for people working in the social sciences.
- Identify the three types of models and describe their characteristics.

Why Statistics Matters

Although many students would not choose to take a statistics course, nearly every social science department requires its students to take a statistics course (e.g., Norcross et al., 2016; Stoloff et al., 2010). Why? Apparently, the professors in these departments think that statistics is essential to their students' education, despite what their students may think.

The main reason why many students must take statistics is that research in the social sciences is dominated by methodologies that are statistics-based; this family of methods is called **quantitative research**. Researchers who use quantitative research convert their data into numbers for the purpose of analysis, and the numbers are then analyzed by **statistical methods**. Numerical data are so important that one social scientist even argued that "progress in science is impossible without numbers and measurement, as words and rhetoric are not enough" (Bouchard, 2014, p. 569).

Quantitative methods – and therefore statistics – dominate most of the behavioral sciences: psychology, sociology, education, criminal justice, economics, political science, and more. Most researchers working in these fields use statistics to test new theories, evaluate the effectiveness of treatments and programs, and learn about the concepts they study. Even workers who do not conduct research must understand statistics in order to understand how (and whether) to apply scientific knowledge in their daily work. Without statistics a practitioner risks wasting time and money by using ineffective products, therapies, or procedures. In some cases, this could lead to violations of ethics codes, accusations of malpractice, lawsuits, and harm to clients or customers. Even students who do not become scientists may need statistics to verify whether an anecdotal observation (e.g., that their company sells more products after a local sports team wins a game than after a losing one) is true. Thus, a mastery of statistics is important to many people, not just researchers and social scientists.

There are four main ways that practitioners use statistics in their work in the social sciences:

1. Separating good research from bad
2. Evaluating the conclusions of researchers
3. Communicating findings to others
4. Interpreting research to create practical, real-world, results.

There is some overlap among these four points, so some job tasks will fall into more than one category. Nevertheless, this is still a useful list of ways that professionals use statistics.

Separating good research from bad is important for any practitioner. The quality of the research published in scientific journals varies greatly. Some articles become classics and spark new avenues of scholarly investigation; others report shoddy research. The fact that a study was published in a scientific journal is not, by itself, evidence of good-quality scientific work. A knowledge of statistics is one of the most important tools that a person can have in distinguishing good research from bad. Having the ability to independently judge research prevents practitioners from being susceptible to fads in their field or from wasting resources on practices that provide few benefits.

The benefits of separating good research from bad research are important for the general public, too, not just practitioners. Most people rely on reports from the news media and the Internet to learn about scientific findings. However, most journalists are not trained scientists and do not have the skills needed to distinguish between a high-quality study and a low-quality one (Yettick, 2015). Readers with statistical training will be able to make these judgments themselves, instead of relying on the judgment of a journalist or social media contacts.

Statistical savviness can also help people in *evaluating researchers' conclusions*. Ideally, the conclusions in a scientific article are supported by the data that the researchers collected. However, this is not always the case. Sometimes researchers misinterpret their data because they either used the wrong statistical procedures or did not understand their results. Having statistical competence can prevent research consumers from being at the mercy of the authors and serve as an independent check on researchers.

Another way that people employed in the social sciences use statistics is in *communicating findings and results to others*, such as their clients and colleagues. Increased global competition now means that stakeholders are demanding evidence that the services they receive are effective. Government entities, insurance companies, school districts, and customers are now more likely than ever to demand that people working in the social sciences use "evidence-based practices," meaning that practitioners are expected to use techniques and tools that are supported by scientific evidence (Capraro & Thompson, 2008). Workers who can understand statistics are at an advantage in this type of environment because they will be able to collect and analyze the data that show that their work is effective. But without statistical data, even the best therapist, teacher, or sociologist could appear to be ineffective – perhaps even incompetent.

Finally, people working in the social sciences must be able to use statistics in *translating research into day-to-day practice*. Because most social science research is quantitative, this means understanding statistical analyses and interpreting them in a way that is relevant to their work. Without statistics, practitioners will not be able to understand or implement new therapies, interventions, or techniques. In time these practitioners' work could become outdated or obsolete.

The Quantitative Research Process. The quantitative research process may take many forms, but generally it requires the researcher to follow these steps:

1. Form a research question or research hypothesis
2. Define the population of interest
3. Select a sample of population members
4. Choose variables to measure and operationalize them
5. Select independent and dependent variables
6. Collect data on the variables
7. Analyze the data with statistics and test the hypothesis to determine whether it is supported by the data.

This is a simplified outline, but it is really all that we need to know to understand statistics. Most students take a research methods course after their statistics course that will explain the research process in detail (Norcross et al., 2016; Stoloff et al., 2010). (And if your department doesn't require a research methods course, you should definitely sign up for one anyway!)

The first step in the scientific research process is to form a **research question** or **research hypothesis**. A research question is the question that a research study is designed to answer. For example, in a fascinating sociological study, Lieberson and Mikelson (1995) were interested in the ways that some parents invent original names for their children. They had a central research question: "Do parents who create names do so in such a way that the names still convey their child's gender?" (Lieberson & Mikelson, 1995, p. 933). The researchers understood that – from a sociological perspective – new parents do not randomly create names. Rather, a child's name often communicates information, and one of the most fundamental pieces of information that a name can convey is the child's gender. Therefore, they wanted to learn if invented names communicate information, so they posed their research question and designed their study to answer it. (The results indicated that strangers *can* usually guess the gender of a child with an original, unique name.)

A **hypothesis** is similar to a research question, but, rather than a question, a research hypothesis is a testable belief that researchers have about the outcome of their scientific study. For example, one Canadian research team (Barnsley & Thompson, 1988) studied the impact that a child's birth date had on the likelihood that they would play hockey on an elite youth team. In Canada, many youth hockey leagues require athletes to reach a certain age by January 1, meaning that players with birthdays early in the year would be larger and taller – because they are older – than players with later birthdays. A previous study (Barnsley et al., 1985) had shown that there were more than about four times more professional hockey players born in January, February, and March than were born in October, November, and December. Therefore, the researchers hypothesized that this trend towards hockey players having birthdays in the beginning of the year would also be apparent in elite youth teams. (Their hypothesis was supported by the research.)

These two examples show an important distinction between research questions and research hypotheses. Research questions tend to be more exploratory, and researchers usually ask research questions when they have little or no basis on which to make an educated guess about the results of their study. On the other hand, research hypotheses are expected results that a researcher has, and this expectation is often formed on the basis of previous research or theory.

A research hypothesis is more than just a belief about the world. To be scientific, a hypothesis must be falsifiable, or possible to disprove. If it is impossible to design a study that would produce results that would disprove the hypothesis, then the hypothesis is not scientific (Popper, 1935/2002). For example, one of the reasons that Freud's theory of psychoanalysis is unscientific is that it is impossible to devise an experiment that would produce results that would show the theory to be untrue. Instead, Freud (and, in later years, his followers) always had some sort of explanation for behaviors that seemed – at first glance – to contradict his theory (Cioffi, 1998). They built up an entire body of ideas that could explain away any apparent evidence that disproved the theory. For example, Freud claimed that male clients who said they did not have a desire to murder their father and marry their mother were using a "defense mechanism" called denial, and the very use of this defense mechanism supported Freud's theory. But not using the defense mechanism (and admitting to these desires about one's parents) would also support psychoanalytic theory. No matter what a person does, it supports the theory. Therefore, there was no way to disprove the theory, making it unscientific.

In contrast, a falsifiable theory could be found to be untrue. If the theory were untrue, then evidence could emerge that would disprove it – forcing scientists to suggest other interpretations of the data. On the other hand, when a falsifiable theory withstands attempts to disprove it, the theory is strengthened and becomes more believable. For example, in one famous article, Miller (1956) proposed that people's working memory had a limited capacity, which was "seven, plus or minus two" (p. 81) and that people would have a great deal of difficulty remembering a longer list of items without a memory aid (e.g., writing things down, using a mnemonic device). This theory is quite easy to test: all it requires is finding the limits of what a person can remember in a short period of time and seeing if they do more poorly when a list exceeds 5–9 items. Despite efforts to disprove this theory, it has held up well and led to an increased understanding of human memory (e.g., Baddeley, 2003) and improved educational practices (e.g., Paas et al., 2003). Likewise, Barnsley and Thompson's (1988) hypothesis that elite youth hockey players would be born earlier in the calendar year is easily falsifiable. For example, if these elite hockey players had birthdays evenly distributed throughout the year, or if most birthdays were at the end of the year, then it would falsify the hypothesis. Thus, the hypothesis that better hockey players are born earlier in the year is a scientific hypothesis.

The second step in this process is to define the **population** of interest. A population consists of every person, event, or object that a researcher could wish to study. The choice of a population is completely at a researcher's discretion. For example, criminal justice researchers could define their population as all crimes committed in Australia in a year. Family science researchers may define their population as all children whose biological parents are divorced or had never married. Psychologists may define their population as every person who suffers from anorexia nervosa. In the social sciences, populations usually consist of people, although they do not have to.

The third step in the quantitative research process is to select a sample from the population. Many populations have millions of people in them, and the constraints of money and time may make it infeasible to gather data from every person in the population. Moreover, studying people means that often we don't have data on every person in a population because some people may refuse to participate in a study, and it is not ethical to force them to participate. Because of these limitations, quantitative researchers in the social sciences almost always select a **sample** of population members to study. A sample is a subset of the population that the researcher collects data from. Ideally, a researcher has a sample that is representative of the population at large, so that the data gathered from the sample can teach the researcher about the entire population.

Sidebar 1.1 Example of a research design

Here is an example that should clarify the nature of quantitative research. Many psychologists are interested in personality because they believe it consists of a set of stable traits that influence how a person acts in different circumstances. In one study (Barrick et al., 2002), psychologists chose to measure extraversion – which is the degree to which a person is outgoing – and job performance. They wanted to test their belief – i.e., their research hypothesis – that people with higher levels of extraversion would be better at their jobs. The operational definitions of these two variables were rather straightforward: an extraversion score obtained from a pencil-and-paper test and a supervisor's rating (on a scale from 1 to 7) of the person's job performance. Psychologists believe that personality is a stable trait through the life span, so it seems unlikely that people's job performance would affect or change their personality. It is much more likely that differences in people's personalities would lead to differences in job performance. Therefore, in this example, extraversion (a personality trait) is an independent variable, and job performance is a dependent variable.

After operationalizing their variables and deciding which variable would be the independent variable and which would be the dependent variable, the researchers collected their data. They found that their belief about extraverted people being better at their jobs was supported by the results of their statistical analyses.

This is an oversimplified description of the study. The authors were interested in more than two variables, and some of their statistical analyses were more sophisticated than anything in this book. But this summary serves as a good explanation of the quantitative research process.

In the fourth step of the process, after selecting a sample a researcher collects data on specific variables. A **variable** is a characteristic that sample or population members can differ on. For example, in Sidebar 1.1, the researchers were interested in extraversion and job performance. These are both variables because some sample members in the study were more extraverted (i.e., outgoing) than others, and some sample members were better at their jobs than others. It is the variation among the sample members that makes both these characteristics variables. However, a characteristic that is the same for all sample or population members is called a **constant**. In the example, a constant may be the species that the sample members belonged to. Because all of them were human and there is no variability among sample members on this trait, this is a constant.

The fifth step of the research process is to choose independent and dependent variables. The **dependent variable** is the outcome variable in the study. The **independent variable** is the variable that is believed to cause changes in the dependent variable. Often social scientists create a design that permits them to have total control over the independent variable, but this is not always possible. After the variables are chosen, it is necessary to operationalize the variable. An **operationalization** is a researcher's definition of a variable that permits a researcher to collect quantitative data on the variable. Operationalization is very common in the social sciences because many of the things that social scientists are interested in – personality, anger, political opinions, attitudes, racism, and more – are not inherently expressed as numbers. Therefore, it is necessary for researchers to create a definition of a variable that can allow them to collect numerical data. An example of an operationalization is counting the number of times a teacher reprimands a child as a measure of how disruptive the child is in class. Other common operationalizations in the social sciences include scores on a test (as in Sidebar 1.1), ratings of the subject's behavior, and measuring the time a person takes to complete a task.

The majority of quantitative research in the social sciences can be classified as experimental research or correlational research (Cronbach, 1957). In **experimental research**, a researcher creates controlled changes in an independent variable in order to learn how those changes affect the dependent variable. On the other hand, in **correlational research**, the researcher does not manipulate or control the independent variable; rather, the researcher measures people's existing levels of the independent variable. The study in Sidebar 1.1 (Barrick et al., 2002) is a correlational study because the authors did not change or manipulate people's levels of extraversion.

Both kinds of research designs have their benefits and drawbacks. Experimental research designs give scientists more control over their subjects and data, and often experimental research permits more conclusions about cause-and-effect relationships (see Sidebar 12.4). However, because it is frequently laboratory-based, experimental research is often criticized for being too artificial. On the other hand, correlational research is often very applicable to real-life situations, but, because of the poor control over the data, researchers usually cannot draw strong conclusions about why variables are related to each other or whether one variable can cause changes in another (Cronbach, 1957).

This classification and the discussion of experimental and correlational research is simplified. Other common designs include descriptive research and quasi-experimental research. Descriptive research describes variables and often does not attempt to investigate relationships among variables. Opinion polls are a common example of this type of research. Quasi-experimental methods are a hybrid between experimental and correlational designs, where researchers attempt to manipulate a variable but may not have complete control over it (as when subjects choose whether to participate in an intervention or control group). In a research methods class, you will learn more about these research designs and perhaps additional important ones, such as single-case designs and qualitative research.

The sixth step in the quantitative research process is to collect data. The mechanics of data collection are beyond the scope of this book, but it is necessary to mention that it is one of the steps of quantitative research. Finally, the seventh and last step is to analyze data using statistics. Most of this book will be concerned with this last step in the quantitative research process.

Qualitative Research. Although quantitative research is the predominant methodology in the social sciences, it is important to mention the principal alternative to quantitative research: a methodology called **qualitative research**. Researchers who specialize in qualitative research believe that it is not beneficial to convert data about their sample members into numbers because most people do not experience their world through numbers. For example, in response to the Barrick et al. (2002) study (see Sidebar 1.1), a qualitative researcher would say that it is nonsensical and too simplistic to convert a person's job performance into a number ranging from 1 to 7. Instead, a qualitative researcher might interview the subject's supervisor to learn which aspects of the job the person excels at and how the person views the work experience. The researcher would then analyze the text of the interview transcript to learn about the nuances of the person's experience. Qualitative methods are popular in anthropology, family science, and some branches of education, psychology, and political science. However, because qualitative research is a methodology that intrinsically rejects numerical data, we will not discuss it further in this book. Nevertheless, you should be aware that qualitative methodologies are valuable in answering questions that quantitative methods cannot.

Mixed Methods. Qualitative and quantitative research each have their own strengths and weaknesses, which are generally complementary. In other words, the questions that quantitative research is not capable of answering (e.g., about how people derive meaning from their life experiences) are the questions that qualitative research is excellent at answering. The reverse is true: quantitative research is best equipped to answer questions that qualitative research cannot (such as the frequency that people with depression miss work due to mental health reasons). For this reason, some researchers find value in combining qualitative and quantitative research into one larger study. This approach is called **mixed methods research**.

Mixed methods research is often valuable because the strengths of quantitative research can compensate for the weaknesses of qualitative research – and vice versa. For example, quantitative research is excellent at producing results that can apply to many different situations and groups of people. But quantitative data are often very narrow in meaning, and the numbers are divorced from the research subjects' everyday experiences. On the other hand, qualitative research tends to be very contextual and often does not apply to other groups of people. However, qualitative data are rich in meaning and provide a great deal of insight into the lives and perceptions of the research subjects. Combining both methods can produce stronger research than a study based on qualitative or quantitative methods alone. Mixed methods may also lead to insights that cannot be obtained from either qualitative or quantitative methods separately (Creswell, 2015).

One downside with mixed methods research is that it requires mastering both qualitative *and* quantitative methods – which is no easy task. Sometimes qualitative and quantitative researchers team up for mixed methods research, which relieves any one person from mastering both research strategies. But a more fundamental problem of mixed methods research is that the underlying philosophies of qualitative and quantitative research are sometimes contradictory. How to combine research that fundamentally rejects numerical data as being valuable (i.e., qualitative research) with data and analyses methods that rely solely on numbers (i.e., quantitative research) can be a major challenge. For these reasons, mixed methods research is not as common as it perhaps should be.

Check Yourself!

- What are the four reasons why a student majoring in the social sciences needs to take a statistics course?
- What are some of the possible consequences for a practitioner who does not understand statistics?
- Explain the difference between an independent variable and a dependent variable.

- What is the difference between qualitative and quantitative research?
- Why is operationalization necessary in the quantitative research process?
- What is the relationship between a sample and a population?

Two Branches of Statistics

As the science of quantitative data analysis, statistics is a broad field, and it would be impossible for any textbook to cover every branch of statistics while still being of manageable length. In this book we will discuss two branches of statistics: descriptive statistics and inferential statistics. **Descriptive statistics** is concerned with merely describing the data that a researcher has on hand. Table 1.1 shows an excerpt from a real collection of data from a study (Waite et al., 2015) about the sibling relationships in families where a child has an autism spectrum disorder. (We will discuss this study and its data in much more detail in Chapters 3, 4, and 10.) Each row in the dataset represents a person and each column in the dataset represents a variable. Therefore, it is apparent that Table 1.1 has 13 people and 6 variables in it. Each piece of information is a **datum** (plural: **data**), and because every person in the table has a value for every variable, there are 78 data in the table (13 people multiplied by 6 variables = 78 data). A compilation of data is called a **dataset**.

Table 1.1 Example of quantitative dataset (from Waite et al., 2015)

Gender	Am satisfied with sibling relationship	Believe that the sibling understands the respondent well	Believe that the sibling understands respondent's interests	Subject worries about their sibling with autism	Believe that parents treated the sibling with autism differently
Female	5	4	3	5	1
Female	5	4	4	1	3
Female	5	5	5	4	5
Female	5	4	2	5	3
Male	3	4	3	5	4
Female	3	1	1	4	5
Male	4	2	2	5	4
Female	4	4	3	4	4
Male	2	2	2	5	5
Female	4	3	3	4	3
Female	5	3	4	5	4
Male	3	2	2	4	5
Female	5	3	4	1	4

Note. In this table, 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree.

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Sidebar 1.2 Terminology

The term "statistics" has two major meanings. The first meaning of "statistics" is the science of data analysis. The second meaning of "statistics" refers to the procedures of an analysis, which are often used to estimate population parameters (Urbina, 2014).

Even though the dataset in Table 1.1 is small, it is still difficult to interpret. It takes a moment and a little effort to ascertain, for example, that there are more females than males in the dataset, or that most people are satisfied with their relationship with their sibling with autism. Table 1.1 shows just an excerpt of the data. In the study as a whole, there were 45 variables for 13 subjects, which totals to 585 data. No person – no matter how persistent and motivated they are – could understand the entire dataset without some simplification. This is actually a rather small dataset. Most studies in the social sciences have much larger sample sizes. The purpose of descriptive statistics is to describe the dataset so that it is easier to understand. For example, we could use descriptive statistics to say that in the range of scores on the variable that measures people's satisfaction with their sibling relationship, the average score is 4.1, while the average score on the variable measuring whether the sibling with autism understands the respondent's interests is 2.9. Chapters 2–5 are concerned with descriptive statistics.

On the other hand, if a researcher only has sample data on hand, descriptive statistics tell the researcher little about the population. A separate branch of statistics, termed **inferential statistics**, was created to help researchers use their sample data to draw conclusions (i.e., inferences) about the population. Inferential statistics is a more complicated field than descriptive statistics, but it is also far more useful. Few social scientists are interested just in the members of their sample. Instead, most are interested in their entire population, and so many social scientists use inferential statistics to learn more about their population – even though they don't have data from every population member. In fact, they usually only have data from a tiny portion of population members. Inferential statistics spans Chapters 6–15 of this book.

An example of a use of inferential statistics can be found in a study by Kornrich (2016). This researcher used survey data to examine the amount of money that parents spend on their children. He divided his sample into five groups, ranked from the highest income group to the lowest income group. He then found the average amount of money that the parents in each group spent on their children and used inferential statistics to estimate the amount of money each group in the population would spend on their children. Unsurprisingly, richer parents spent more money on their children, but Kornrich (2016) also found that the gap in spending on children between the richest 20% and poorest 20% of families had widened between 1972 and 2010. Because Kornrich used inferential statistics, he could draw conclusions about the general population of parents – not just the parents in his sample.

Check Yourself!

- What is the purpose of descriptive statistics?
- What is the purpose of inferential statistics?
- How is inferential statistics different from descriptive statistics?

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Models

This book is not organized like most other textbooks. As the title states, it is built around a **general linear model** (**GLM**) approach. The GLM is a family of statistical procedures that help researchers ascertain the relationships between variables. Chapter 7 explains the GLM in depth. Until then, it is important to understand the concept of a model.

When you hear the word "model," what do you think of? Some people imagine a fashion model. Others think of a miniature airplane model. Still others think of a prototype or a blueprint. These are all things that are called "models" in the English language. In science, **models** are "simplifications of a complex reality" (Rodgers, 2010, p. 1). Reality is messy and complicated. It is hard to understand. In fact, reality is so complex – especially in the social sciences – that in order for people to comprehend it, researchers create models (Smaldino, 2017).

An example from criminology can illustrate the complexity of reality and the need for models. One of the most pressing questions in criminology is understanding who will commit crimes and why. In reality, it is impossible to comprehend every influence that leads to a person's decision to commit a crime (or not). This would mean understanding the person's entire personal history, culture, thoughts, neighborhood, genetic makeup, and more. Andrews and Bonta (2010) developed the risk–need–responsivity (RNR) model of criminal conduct. Although not its only purpose, the RNR model can help users establish the risk that someone will commit a crime. Andrews and Bonta did not do this by attempting to understand every aspect of a person. Rather, they have chose a limited number of variables to measure and use those to predict criminal activity. Some of these variables include a history of drug abuse, previous criminal behavior, whether the person is employed, the behavior of their friends, and the presence of certain psychological diagnoses (all of which affect the probability that someone will commit a crime). By limiting the number of variables they measured and used, Andrews et al. created a model of criminal behavior that has been successful in identifying risk of criminal behavior and reducing offenders' risk of future reoffending after treatment (Andrews et al., 2011). This model – because it does not contain every possible influence on a person's criminal behavior – is simplified compared to reality.

This example illustrates an important consequence of creating a model. Because models are simplified, every model is – in some way – wrong (Smaldino, 2017). Andrews and Bonta (2010) recognized that their model does not make perfect predictions of criminal behavior every time. Moreover, there are likely some influences not included in the RNR model that may affect the risk of criminal behavior, such as a cultural influence to prevent family shame or the dying request of a beloved relative. There is a trade-off between model simplicity and model accuracy: simpler models are easier to understand than reality, but this simplification comes at a cost because simplicity makes the model to some extent wrong. In a sense, this is true of the types of models most people usually think about. A miniature airplane model is "wrong" because it often does not include many of the parts that a real airplane has. In fact, many model airplanes don't have any engines – a characteristic that definitely is *not* true of real airplanes!

Because every model is wrong, it is not realistic to expect models to be perfectly accurate. Instead, models are judged on the basis of how *useful* they are (Box, 1976; Smaldino, 2017). A miniature model airplane may be useless for understanding how a full-sized airplane works, but it may be very helpful for understanding the aerodynamic properties of the plane's body. However, a

