PATTERNS OF USE AND ATTITUDES TOWARDS STATISTICS IN PSYCHOLOGICAL PROFESSION: A CROSS SECTIONAL STUDY

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Final Thesis

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1. Introduction

Modern statistics has been a part of experimental psychology since the late 1800s, even though it was not yet incorporated into psychological education. Statistical methods took place in the field decades before its incorporation into, for example, economics and sociology (Stigler, 1992). These methods allowed psychology to transition from a philosophical discipline into a scientific and empirical field. Today, statistics plays an important role in psychological research, guiding the formulation of hypotheses, data analysis, and interpretation of findings. Apart from research, diagnostic tools and tests could not be designed or interpreted without adequate statistical skills. Statistics education serves the ultimate goal of producing statistically literate individuals who possess the ability to effectively apply statistical thinking (Ramirez et al., 2012). This is particularly important in psychology, where analyzing and interpreting data is essential to research and evidence-based practice.

Therefore, statistical courses have been one of the fundamental courses in psychology programs. On the other hand, students frequently consider it one of the most difficult and unwanted subjects in psychological education (Green et al., 2015). In the study done by Green et al. (2015), the authors stated that statistics might be an unwanted subject among psychology students due to the classification of psychology as a “soft” discipline. In that view, the term "soft" discipline refers to academic fields that are perceived to rely more on subjective interpretations and less rigorous scientific methods. This perception of the field later leads students to be resistant when they enroll and notice the emphasis placed on scientific methodology and statistics in instruction (Freng et al., 2011). Furthermore, studies have shown that students' interests are most commonly in non-research courses, such as human-interest courses like psychopathology and personality psychology, and far less in research-oriented courses like research methods and statistics (Hixenbaugh et al., 2006; Lloyd-Lewis et al., 2023). Literature also suggests that, in general, statistics is not a popular topic of interest to psychology majors (Rajecki et al., 2005). Lloyd-Lewis et al. (2023) have found that students' poor interest in methodology courses could be due to their perception of research subjects being too difficult, requiring skills they do not possess, and lacking relevance to their future studies and careers. From these findings, it may be concluded that students do not consider statistics as directly practically applicable in the everyday work of a psychologist. Even though statistics has been integrated into psychological education since the 1940s (Nuttgens, 2023), the use of and attitudes about statistics in practicing psychologists have not been widely researched.

The current state of statistical education in undergraduate psychology

Statistics modules are among the most problematic for psychology students due to superficial teaching, lack of linking theory with practice, unfamiliarity with concepts, constituting an integrated picture of the parts of scientific research, and their negative attitudes toward quantitative methods courses (Murtonen et al., 2008). Furthermore, the TARG Meta-Research group (2022) conducted a study examining multiple statistics module syllabi among undergraduate psychology programs in the United Kingdom. Most module hours were allocated to workshops, labs, or practicals. Considering the software types used, they have found that most psychology programs focus on conventional software use, such as SPPS, rather than open-source software like R. This study also found that, when it comes to statistics education, psychology programs focus mostly on inferential statistical tests and not on a deeper understanding of data and data skills. Many did not mention key statistical tools and concepts whose use researchers and statisticians increasingly encourage, such as statistical power, effect size, confidence intervals, and reproducibility.

In Croatia, psychology programs incorporate a wide range of statistics and methodology courses, taking about one-third of all ECTS points of undergraduate mandatory courses. Different studies seem to suggest that appropriate changes do not follow the rapid advancement in technology in teaching practices, although computer-assisted technology in teaching statistics to undergraduate psychology students may be beneficial for their understanding of the relevant concepts (Lloyd & Robertson, 2011). Apart from advances in teaching related courses, instructors should emphasize the importance of research in all areas of psychology (Robertson et al., 2011; Ruggeri et al., 2008), particularly areas of high interest perceived by psychology students (Lloyd-Lewis et al., 2023).

Attitudes toward statistics in psychology

Despite the importance of statistics in psychology, there is variability in the valence of attitudes toward statistics, and how individuals engage with statistical techniques. A study by Dempster and McCorry (2009) found that psychology students' approaches to statistics are associated with factors such as educational background, professional experience, and individual characteristics. More specifically, these factors were correlated with their statistical performance and engagement, indicating that positive attitudes towards statistics, shaped by prior experiences and personal traits, are associated with better outcomes in statistics courses. Research on student attitudes toward statistics has been a topic of interest for numerous studies in psychology and most have shown that students have negative perceptions of the course

(Conners et al., 1998; Hogg, 1991; Ruggeri et al., 2008; Schutz et al., 1998). These negative perceptions of students are reflected in poor interest in the course, and overall not enjoying the course itself (Judi et al., 2011). On the other hand, Coetzee and Van der Merwe's (2010) study found that although students viewed statistics as technical and difficult, they recognized its value and expressed interest in the subject. Moreover, Eccles and Wigfield (2002) found that the value placed on an educational task significantly predicted students' engagement and performance in that task. Overall, a positive attitude ensures the application of learned knowledge and encourages the pursuit of further learning opportunities.

The perceived usefulness and relevance of statistics have been linked to students' engagement and performance in statistics courses, suggesting that attitudes toward statistics are associated with the learning and application of statistical methods (Ramirez et al., 2012). Consequently, apart from the obtained knowledge, attitudes are considered one of the most important outcomes of introductory statistics courses. These findings suggest that attitudes toward statistics might predict the use of statistics. However, since most previous studies on the topic were conducted on students (Counsell & Cribbie, 2020; Dempster & McCorry, 2009; Judi et al., 2011; Landa-Blanco & Cortés-Ramos, 2021; Ramirez et al., 2012), expanding the view on practicing psychologists could help understand how these attitudes are linked to their everyday job requirements involving statistics. Understanding how attitudes are linked with the use of statistics in psychologists' work could further aid the development of psychology programs' statistical education that is more in line with psychological practice. Moreover, exploring attitudes towards statistics of practicing psychologists could inform the development of effective training programs aimed at increasing statistical literacy among psychologists, ultimately improving the quality and accuracy of research and other aspects of statistical utility in the field.

Recommendations for the improvement of statistical education

Understanding the use of and attitudes toward statistics in psychology could create a different perspective on statistics within psychological education. This could encourage the development of possible changes to the curriculum, aiming to make it more suitable for the needs of the profession. Various studies report a need to improve statistical education in the psychological profession, suggesting a need for reform (Anglin & Edlund, 2019; Badenes-Ribera et al., 2016, 2018). Badenes-Ribera et al. (2016) suggest that reform is needed in terms of evidence-based practice, advocating for the practical application of statistical knowledge, which implies a better interpretation of the results. These might be achieved by introducing students to novel ways of computing statistical analyses, as well as the practical application of the obtained knowledge (Counsell et al., 2016). There is no doubt whether statistics is important in the field itself, but how it is taught and the concepts that are learned in the courses may need a change to better aid future usage in the profession itself (Thibault et al., 2024). For example, a study conducted by Thibault et al. (2024) found a consensus among professionals regarding their recommendations for the improvement of statistical education. They agreed that students should learn to understand data, formulate a research design, calculate descriptive and inferential statistics, and gain the knowledge needed for critical assessment of research data and methodologies. Incorporation of the practical application of learned materials could naturally enhance these skills, as students would gain hands-on experience in real-world scenarios, reinforcing theoretical knowledge and developing their competence in applying these skills effectively (Fantinelli et al., 2024; Hutter et al., 2016). However, there was no consensus regarding the importance of learning advanced research techniques, computer skills, or module format. That is, psychologists do not believe that psychology programs should emphasize teaching advanced research techniques, and computer skills or that the format of the course learned is an important aspect of students' education (Thibault et al., 2024).

Currently, many psychology courses rely on calculation exercises to transfer statistical skills to students. It has been noted that this might be a suboptimal form of teaching. For example, studies have shown that shifting instructional focus away from hand calculations towards using software like R could significantly improve students' statistical reasoning and comprehension (Ditta & Woodward, 2022; Pirlot & Hines, 2023). Considering the application of software as a part of statistical education, researchers have pointed out that it would be beneficial to use open-source software, such as R or JASP, for students to gain adequate statistical knowledge needed for the understanding and interpretation of statistics (Counsell & Cribbie, 2020; TARG Meta-Research Group, 2022). Open-source software offers several advantages over conventional software, including free access, continuous updates and improvements, as well as flexibility and customizability that allow students to tailor their learning to specific needs, enhancing their practical skills and adaptability in real-world applications (Duan & Lee, 2022). Furthermore, a study by Counsell and Cribbie (2020) found that while introductory-level students had neutral attitudes, students at higher levels had somewhat positive attitudes toward both R and statistics. The authors suggest that R is suitable for undergraduate psychology students, offering benefits such as free access, flexibility, a wide range of statistical analyses, and enhanced data analysis skills, whereas challenges include a steep learning curve, initial complexity, and the need for instructors to be proficient in R to provide adequate support. This study also highlights the importance of instructors in shaping students' attitudes toward the subject, encouraging instructors to focus on making the learning experience more engaging and accessible and providing adequate support and resources. Also, considering the technological advancement and rapid development of various software packages, it has been noted that statistics instructors should be aware of the downsides in teaching how to use sophisticated software packages, making students spend more time learning how to use them rather than applying the learned material (Chance et al., 2007).

The rationale for this study

A need for reform in statistical education within psychology reflects a growing recognition of the importance of statistics in the field. This emphasizes the need for a curriculum that equips future professionals with adequate job-related skills. While most of the studies that investigated attitudes toward statistics have focused on the attitudes of students (Counsell & Cribbie, 2020; Dempster & McCorry, 2009; Judi et al., 2011; Landa-Blanco & Cortés-Ramos, 2021; Ramirez et al., 2012), there is a gap in the exploration of attitudes and patterns of use among graduated practicing psychologists. Additionally, there has been no such study among graduated psychologists in Croatia. Gaining a deeper understanding of patterns of use and attitudes towards statistics among Croatian practicing psychologists might provide insights into psychologists' perceptions of statistical analyses' utility, relevance, and challenges. Obtaining direct feedback from the professionals who work in psychology could further aid the understanding of statistical procedures and tools needed to develop adequate skills in the field itself.

Overall, this study aims to provide a deeper understanding of the role of statistics in everyday psychological practice. It focuses on identifying professionals' recommendations for improving statistical education in psychology programs. Additionally, it seeks to examine which components of attitudes toward statistics predict its use in professional work. The insights gained from this research can be used to advance evidence-based practices within psychological education. Furthermore, the findings could offer directions for improvements in psychologists' statistical competence and education by identifying trends and barriers in statistical use, thus bridging the gap between education and everyday practice.

1.1. Objectives

1.1.1. Research Aims

RA1: To examine if the components of attitudes towards statistics predict the use of statistics in psychologists' work.

RA2: To investigate psychologists' suggestions for improving statistical education within psychology programs.

1.1.2. Hypotheses

H1: Practicing psychologists' use of statistics in their work will be predicted by their attitudes toward statistics. More specifically, a higher percentage of use will be predicted by higher affect scores, greater perceived cognitive competence, greater perceived value, lower perceived difficulty, higher interest, and higher effort invested into statistics.

H2: The most prevalent recommendations for improving statistical education in psychology among practicing psychologists will be to implement practical applications and user-friendly software.

2. Methods

Study Design

This was a cross-sectional study (https://osf.io/bh36x). A survey approach was utilized and conducted in January, February, and March of 2024.

2.1. Instrument Description

The survey tool contained a total of 60 questions separated into 4 sections. Along with demographic variables, use and knowledge of statistics, and questions used to measure recommendations and study experience, we used a modified version of Survey of Attitudes Toward Statistics (SATS-36) (Schau, 2003) to measure participants' attitudes towards statistics. To utilize the SATS-36 scale in our study, we contacted the author and obtained her consent. The survey was distributed in Croatian and later back-translated into English.

Demographic Characteristics

Demographic characteristics measured were: Sex (*Sex:*), Age (*Age in years*), Doctorate (*Do you have a completed Ph.D.?*), Place of study (*Did you obtain your degree in Croatia or abroad?*), University (*If you obtained your degree in Croatia, please select the institution where you completed your graduate studies in psychology.*), Country (*If you finished your study abroad, please state the country.*), Field of work (*In which field of psychology do you primarily work?*), Years from graduation (*How many years have passed since you finished your studies?*), Years of work (*How many years have you been working in psychology?*).

Use and Knowledge of Statistics

Participant's use of statistics was measured by asking them several questions regarding the use of statistics in their work. The measured variables were; Categories of use of statistics (*Can you list all the activities in your professional work for which you use statistics?*), Percentage of use of statistics (*For the activities you mentioned previously, in what percentage of your working time do you do that?*), Statistical package usage (*Do you know how to use any statistical packages?*), Statistical packages used (*When you do statistical analyses, which packages do you use?*), Confidence in statistics application (*If you were to conduct statistical analysis, how confident are you that you could do it correctly?*), Published research paper (*Have you ever published a research paper?*), Statistics done for the research (*If so, did you do the statistics for that paper yourself?*), Statistics GPA (*What was your average grade in introductory statistics courses?*).

Recommendations and Study Experience

Participants' recommendations for the improvement of statistics education and their study experience were measured with the following variables; Content of statistics education (*Rate the following questions about your study experience based on the frequency of each using percentages (0-100%); how much time was dedicated to: computer use, hand calculations,* and *theory.*), Recommendations for improvement of statistical education (*Select what would, in your opinion, help today's students in learning statistics.*), The most important part of statistics education (*Select what you think is the most important aspect of statistical education.*).

Attitudes toward Statistics

The participants' attitudes toward statistics were measured using the Survey of Attitudes Towards Statistics (SATS-36) (Schau, 2003). The scale consists of 36 items scored on a Likert scale from 1 to 7 (e.g., 1= strongly disagree to 7 = strongly agree). According to the directions of the instrument, the answers to negatively worded items were reversed (1 was replaced by 7, 2 by 6, etc.). The order of items on the scale was randomized to avoid response bias. The SATS-36 measures 6 components of attitudes towards statistics; *Affect* – participants' feelings concerning statistics (6 items); higher scores indicating more positive feelings concerning statistics, *Cognitive competence* – participants' attitudes about their intellectual knowledge and skills when applied to statistics (6 items); higher scores indicating greater perceived intellectual skills when applied to statistics, *Value* – participants' attitudes about the usefulness, relevance, and worth of statistics in personal and professional life (9 items); higher scores indicating greater perceived value of statistics, *Difficulty* – participant's attitudes about the difficulty of statistics as a subject (7 items); higher scores indicating a lower perceived difficulty of statistics, *Interest* – participants' level of individual interest in statistics (4 items); higher scores indicating higher level of interest in statistics, and *Effort* - the amount of work the participant expends to learn statistics (4 items); higher scores indicating a greater amount of work invested to learn statistics. Items of each subscale can be found in the Supplement table (Table A). The total scores for each subscale were calculated after reverse coding negatively worded items and summing the scores of items within every individual subscale.

Scale Reliability

Table 1 shows descriptions, number of items (in brackets), and Cronbach alpha coefficients for subscales of the SATS-36 questionnaire for data collected in this study.

Table 1

Reliability of the SATS-36 Subscales

Subscale	Description	Cronbach alpha [95%CI]
Affect	Participants' feelings concerning statistics (6 items)	.87 [.85, .88]
Cognitive competence	Participants' attitudes about their intellectual knowledge and skills when applied to statistics (6 items)	.80 [.78, .83]
Value	Participants' attitudes about statistics' usefulness, relevance, and worth in personal and professional life (9 items)	.80 [.77, .82]
Difficulty	Participants' attitudes about the difficulty of statistics as a subject (7 items)	.66 [.60, .69]
Interest	Participants' level of individual interest in statistics (4 items)	.85 [.83, .87]
Effort	Amount of work the participant expends to learn statistics (4 items)	.72 [.68, .76]

2.2. Data Collection Methods

Piloting and Refinement

To refine the survey, we used a sample of psychology students (n=5) and academic psychologists (n=3) to review the questions' comprehensibility and to give us feedback about the survey characteristics.

Data Collection

The data collection method was a combination of purposeful and snowball sampling techniques. The first data collection phase lasted from the last week of January to the middle of February. We collected email addresses of Croatian psychological societies and associations. The sample comprised every county's psychological society in Croatia, as well as other psychological associations. An invitation email was sent a week before the email containing the survey link, followed by a reminder a week later. Out of 53 email addresses, 45 were successfully delivered. The remaining 8 emails could not be delivered due to the recipient's full inbox or address not being found. The link to the survey was also posted on two Facebook groups with Croatian psychologists and a Croatian website with psychology-related content.

The second data collection phase lasted from the last week of February to the second week of March. We went through the directory of licensed psychologists in Croatia and collected individual email addresses that were publicly available via Google search. The named population received one email containing the link to the survey. Out of the 2013 email addresses that were collected, 1893 were successfully delivered. The remaining 120 emails were not delivered due to full inboxes or inactive email accounts. For this phase, the survey was sent without invitations or reminders.

Survey Administration

The questionnaire was made and carried out through the SurveyMonkey software (SurveyMonkey Inc., San Mateo, California, USA, see www.surveymonkey.com). The survey was sent via email. The total number of email addresses to which this survey was successfully delivered was 1938 (out of 2066). Additionally, this survey was posted on two Facebook groups comprised of Croatian psychologists and a Croatian website with psychology-related content.

2.3. Sample Characteristics

The participants in this study were licensed psychologists in Croatia, members of the Croatian Psychological Chamber, who currently work in any field of psychology. Our targeted population consisted of 3733 licensed psychologists in Croatia (https://www.psiholoska-komora.hr/imenik.php), members of the Croatian Psychological Chamber. Participants were excluded from the study if they did not give consent for participation, stopped completing the questionnaire after giving the initial consent, or did not (currently) work in psychology.

Sample Description

We collected a sample of 602 participants out of which 406 completed the whole survey. Out of the initial 602 participants, 17 were excluded from the final analysis, 2 because they did not give consent for the research, 2 because they stated that they did not work in psychology, and 13 because they exited the survey without answering any questions. After the exclusion, we analyzed all data obtained, and the sample sizes could differ between different analyses. A flowchart of the participants in the study can be found in the Supplement (Figure A).

Demographic Characteristics

Participants were predominantly female, did not have a doctorate, and, concerning their place of study, finished their master's degree in Croatia (Table 2). Of those who finished their degree in Croatia, the majority did so at the Faculty of Humanities and Social Sciences in Zagreb, and of those who finished their degree outside Croatia, most of them did so in Italy and Bosnia and Herzegovina (Table 2). Concerning their field of work, most of our participants were school psychologists, followed by clinical and health psychologists (Table 2).

Table 2

Demographic Characteristics of all Participants (Total N= 585)

Variable	Category	n (%)	Median	IQR
Sex				
	Female	540 (92.3)		
	Male	43 (7.4)		
	I prefer not to say	2 (0.3)		
Doctorate				
	No	481 (82.2)		
	Yes	62 (10.6)		
	In process	42 (7.2)		
Place of Study				
	In Croatia	553 (94.5)		
	Outside Croatia	32 (5.5)		
University [a]				
	Faculty of Humanities and Social Sciences in Zagreb	240 (41.0)		
	Faculty of Humanities and Social Sciences in Rijeka	107 (18.3)		
	Faculty of Croatian Studies	74 (12.6)		
	Department of Psychology in Zadar	62 (10.6)		
	Faculty of Humanities and Social Sciences in Osijek	45 (7.7)		
	Catholic University of Croatia	23 (3.9)		
Country [b]				
	Italy	7 (1.2)		
	Bosnia and Herzegovina	7 (1.2)		
	Slovenia	6 (1.0)		
	Serbia	6 (1.0)		
	Other	5 (0.9)		
Field of Work [c]				
	School Psychology	133 (22.7)		
	Clinical and Health Psychology	111 (19.0)		
	Social Care	57 (9.7)		
	System of Science and Higher Education	54 (9.2)		
	Preschool Psychology	41 (7.0)		
	Work and Organizational Psychology	33 (5.6)		
	Occupational Health Psychology	21 (3.6)		
	Penological Psychology	15 (2.6)		
	Psychology in Professional Guidance	11 (1.9)		
	Military Psychology	8 (1.4)		
	Other	23 (3.9)		
Age			38	32-48
Years from Graduation [c]			13	8-24
Years of Work [c]			13	7-23

Note: [a] Missing 2 answers; [b] Missing 1 answer; [c] Missing 78 answers.

2.4. Ethical Considerations

This study was approved by the Ethical Committee Board of the Faculty of Humanities and Social Sciences in Split (Ethical approval number: 2181-190-24-00006, Ethical approval date: January 8, 2024.).

The confidentiality of this study was ensured by taking only information relevant to the study from the participants (doctorate, field of work, age, sex), which was necessary for the analysis of the data and the research results. We did not collect participants' IP addresses.

Additionally, we notified psychological societies and associations that they would be receiving an email with the link for participation in the research. Emails were sent only to the publicly available email addresses. Lastly, on the first page of the survey, we asked for the participants' informed consent. Participants' personal information was not shared in the research; only the researchers were aware of details such as their names and email addresses.

2.5. Data Analysis

The statistical analysis was done with R statistical software (Version 2021.9.0.351; R Core Team, 2021) and JASP (Version 0.18.3; JASP Team, 2024).

Description of Data

Categorical variables were presented as frequencies and percentages. Numerical variables were tested for normality using the Shapiro-Wilk test for normality. Due to the significant deviation from normality ($p<0.05$) variables were presented as medians (*Mdn*) with interquartile range (*IQR*) for the overall sample or as medians with 95% confidence intervals (*CIs*) for subgroups. Descriptive statistics were calculated in JASP, apart from the median 95% confidence intervals which were done in R. Additionally, following the instructions of the instrument used, the scores on items of each subscale of the SATS-36 were calculated using means with 95% confidence intervals and can be found in the Supplement (Table A).

Percentage of Use Prediction

Multiple linear regression analysis was used to assess whether components of attitudes toward statistics predicted the use of statistics in our sample. The model was established using the entry method, with all predictors entered into the model simultaneously.

We conducted several diagnostic tests, including the analysis of standard residuals, collinearity, independent errors, normality of the error distribution, homoscedasticity, linearity, and non-zero variance. We found that most of the assumptions of multiple linear regression were met. One exception was the normality of the residuals, which were handled by removing outliers from the sample. Furthermore, before conducting the regression analysis, we did a correlation analysis to identify and understand the relationship between variables and assess the direction and strength of these relationships. We used the Shapiro-Wilks test for univariate normality to determine which correlation coefficients to use.

The regression analysis was performed in JASP and R software. We used multiple linear regression to assess whether SATS-36 components of attitudes toward statistics predicted the participants' use of statistics in their work. Results were expressed as unstandardized (*b*) and standardized regression coefficients (β) with 95% confidence intervals, along the standard errors of the estimates (*SE*), t-values (t), p-values (p), coefficients of determination (R^2), and F-statistics (F). We calculated the 95% confidence intervals for β using the following equation: $95\%CI=\beta\pm1.96\cdot(\beta/t)$. All analyses were conducted with a significance threshold of $p < 0.05$.

3. Results

3.1. Descriptive Statistics

Use and Knowledge of Statistics

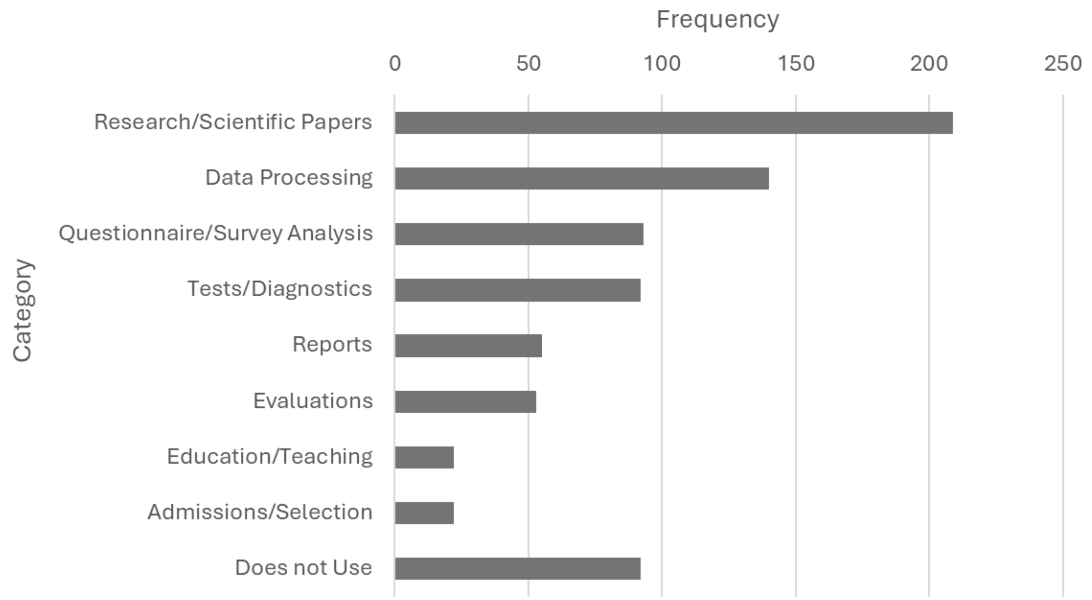
Participants' answers on the categories of use of statistics were coded and categorized. Two evaluators independently coded answers for the first 20 respondents, based on which the rest of the data was coded. Answers could be coded under one or more of the following categories:

1) *Research/Scientific Papers*- using statistics solely for conference attendance and publications, as well as research in the scope of their work;
2) *Data Processing*- using statistics to sort and process the data needed in their work, such as creating tables and sorting the information of their clients;
3) *Questionnaire/Survey Analysis*- using statistics to create questionnaires for their work and analyze the data obtained in the surveys. This differs from the first category because these refer to the use of statistics to analyze the obtained data for non-formal purposes;
4) *Tests/Diagnostics*- using statistics to read and form the data from the clients to compare their results to the general mean of a given condition (mostly in clinical psychology);
5) *Reports*- using statistics to form a report of work to competent authorities, creating general information and work standards;
6) *Evaluations*- using statistics to compare the contents/results of work and events to previous data, to form general conclusions about a program or an institution;
7) *Education/Teaching*- using statistics on an academic level; to pass on statistical knowledge to students;
8) *Admissions/Selection*- using statistics to generate new employees or to enroll children in schools; testing candidate’s competencies or children's capabilities;
9) *Does not Use*- participants’ answers were put in this category if they specifically stated that they do not use statistics in their work or if they marked the question with a sign (e.g. 0 or /).

The frequencies of each coded response are shown in Figure 1. Most participants in our study stated that they use statistics for *Research/Scientific Papers* and *Data Processing*. Along with these two categories, many participants stated that they use statistics for *Questionnaire/Survey Analysis* and that they do not use statistics in their work (*Does not Use*). The lowest number of participants stated that they use statistics for *Education/Teaching* and *Admission/Selection*.

Figure 1

Self-Reported Statistics Use Categories from Open-Ended Responses (Total N=507)



Note: Participants' answers could have been coded under one or more categories.

Most of the participants reported that they know how to use some statistical packages, and out of those most of them stated that they use *SPSS* and *Excel* when doing statistical analyses (Table 3). The least number of respondents selected *STATA, Phyton*, and *Lisrel* as packages that they use (Table 3). Furthermore, most participants stated that they published a research paper, and the majority selected that they did the statistics for their research by themselves (Table 3). Additionally, participants were asked to state in percentages how confident are they that they would do a statistical analysis correctly (Table 3). Participants' average GPA in introductory statistics courses and percentage of use of statistics in their working time are shown in Table 3.

Table 3

Participants' Statistics Use Information (Total N=507)

Variable	Category	n (%)	Median	IQR
Statistical packages usage [a]				
	Yes	413 (81.5)		
	No	94 (18.5)		
Statistical packages used [b]				
	SPSS	334 (81.8)		
	Excel	266 (65.2)		
	Statistica	69 (16.9)		
	R	35 (8.6)		
	JASP	23 (5.6)		
	Jamovi	23 (5.6)		
	Amos	18 (4.4)		
	Mplus	14 (3.4)		
	PSPP	8 (1.9)		
	STATA	4 (0.9)		
	Python	4 (0.9)		
	Lisrel	3 (0.7)		
	Other	13 (3.2)		
Published research paper [c]				
	Yes	305 (60.9)		
	No	196 (39.1)		
Statistics done for the research				
	Yes	235 (77.0)		
	No	70 (23.0)		
Percentage of use of statistics [d]			10	5-25
Confidence in statistics application [d]			60	30-80
Statistics GPA [e]			4	3-4

Note: [a] Missing 5 answers; [b] Participants could select multiple answers; [c] Missing 6 answers; [d] Answers in percentages (0-100%); [e] Missing 78 answers, (2.0-5.0 scale).

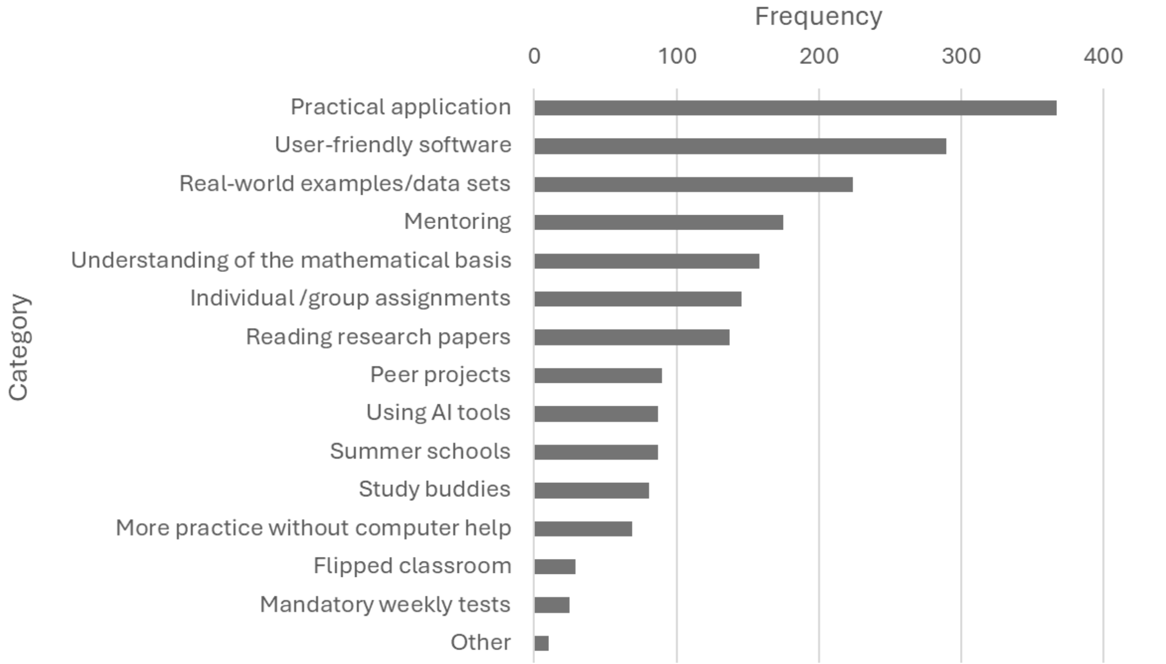
Recommendations and Study Experience

The frequencies of each response are shown in Figure 2. Most participants suggested that *Practical application* and *User-friendly software* would help today's students in learning statistics. The least number of respondents selected *Flipped classrooms* and *Mandatory weekly tests* as something that would help students in learning statistics.

Additionally, participants were asked to select which part of statistical education they think is the most important. Most participants stated that *Practical application* is the most important (n=206), followed by that *All parts are equally important* (n=199), fewer that *Theory* is the most important (n=17), and the least number of participants stated that *Calculation exercises* were the most important part of statistical education (n=3). Lastly, participants were asked to rate on a scale (from 1 to 100%) how much time was dedicated to which part of statistical education in their study. Considering the average of all responses, most of the time was dedicated to *Theory*, followed by *Hand calculations*, and the least amount of time was dedicated to *Computer use* (Table 4).

Figure 2

Frequencies of Recommendations for the Improvement of Statistics Education (Total N=425)



Note: Participants could select multiple answers.

Table 4

Percentage of Time Dedicated to Parts of Statistical Education (Total N=425)

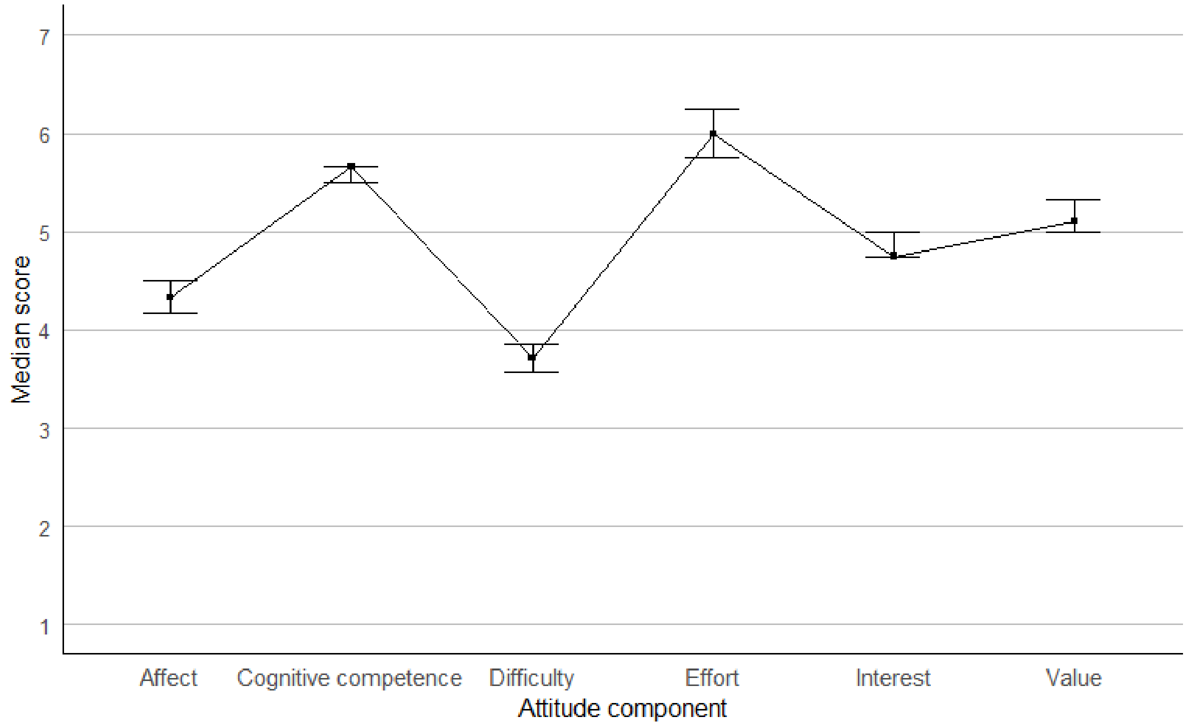
Part of education	Median	IQR
Theory	40	30-50
Hand calculations	33	20-50
Computer use	20	10-40

Attitudes toward Statistics

The SATS-36 questionnaire was comprised of 36 items forming 6 subscales. Means and CIs for each item and subscale can be found in the supplement (Table A). Participants' median scores were the highest for the *Effort* and *Cognitive competence* components of attitudes, and lowest for *Difficulty* and *Affect* components (Figure 3).

Figure 3

Medians and 95% CIs of Scores on SATS-36 Subscales (Total N= 406)



3.2. Percentage of Use Prediction

Assumption Checks

We first wanted to check whether we have the conditions to perform a regression analysis. To assess the strength of the difference between observed and expected values we carried out an analysis of standard residuals. This was done with the assumption that an absolute value of standard residuals greater than 2 was an outlier. The analysis has shown that a total of 18 participants had outlier residuals, so we have removed them from further analysis.

Additionally, to test for multicollinearity we examined the Variance Inflation Factor (VIF) and tolerance values. Our analysis indicated that multicollinearity was not a concern, considering tolerance and VIF (Affect, *Tolerance*=.38, *VIF* = 2.62; Cognitive competence, *Tolerance*=.41, *VIF* = 2.42; Value, *Tolerance*=.52, *VIF*=1.94; Difficulty, *Tolerance*=.71, *VIF*=1.42; Interest, *Tolerance*=.48, *VIF*=2.10; Effort, *Tolerance*= .85, *VIF*=1.18) values were within the recommended values, with VIF being below 5 and tolerance above 0.1 (Kleinbaum et al., 1988).

Furthermore, we tested the assumption of independent errors using the Durbin-Watson (DW) test, with the acceptable range being from 1.5 to 2.5 (Durbin & Watson, 1950). The DW value indicates if the errors are independent of each other, indicating the randomness of the sample. Our data met the assumption of independent errors (*DW value* = 2.05).

Lastly, the histogram of standardized residuals indicated that the data contained approximately normally distributed errors, as did the normal Q-Q plot of standardized residuals, which showed approximately normal points. The Q-Q plot can be found in the supplement (Figure B). Additionally, the scatterplot of standardized residuals showed that the data met the assumptions of homogeneity of variance and linearity. The data also met the assumption of non-zero variances, indicating that there is some degree of variability in the data points for each variable (Affect, *Variance* = 1.93; Cognitive competence, *Variance* = .87; Difficulty, *Variance*= .70; Interest, *Variance* = 2.02; Effort, *Variance*= .83; Percentage of Use, *Variance*=248.38).

Correlation Analysis

Before conducting a multiple linear regression analysis, we calculated bivarieate correlations to identify and understand the relationship between variables and assess the direction and strength of these relationships. Firstly, we checked for normality using the Shapiro-Wilk test for each variable entered into the analysis, which has shown that *Affect* (W=0.986, p<0.01), *Cognitive competence* (W=0.955, p<0.01), *Value* (W=0.979, p<0.01), *Interest* (W=0.973, p<0.01), *Effort* (W=0.929, p<0.01) and the *Percentage of use* (W=0.836, p<0.01) variables were not normally distributed, whereas *Difficulty* (W=0.995, p=0.27) was normally distributed. Because of this, we used Spearman's rho coefficients for the correlation assessment. Table 5 shows the correlation coefficients between the variables.

Table 5

Spearman's Correlations between 6 Attitude Components and the Percentage of Use

Variable	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**
1. Percentage of use	-	-	-	-	-	-	-
2. Affect	0.18**	-	-	-	-	-	-
3. Cognitive competence	0.20**	0.73**	-	-	-	-	-
4. Value	0.45**	0.45**	0.46**	-	-	-	-
5. Difficulty	0.11*	0.42**	0.35**	0.19**	-	-	-
6. Interest	0.35**	0.49**	0.44**	0.66**	0.09*	-	-
7. Effort	0.02	0.06	0.18**	0.07	-0.22	0.19**	-

*Note: * indicates p<0.05; ** indicates p<0.01*

Regression Analysis

Multiple linear regression was conducted to see if components of attitudes toward statistics (Affect, Cognitive competence, Value, Difficulty, Interest, and Effort) predicted the total value of the percentage of statistics used in psychologists' work. Only the participants who answered all questions of the SATS-36 were entered into the analysis (N=406). After controlling for the outliers, the total number of participants entered into the final regression analysis was 388. Overall, the results showed that attitude components explained a significant amount of the variance in the value of the percentage of use of statistics (F (6, 381) = 17.47, p < .001, R^2 = .22). However, only the *Affect* and *Value* components of attitudes significantly predicted the value of the percentage of use of statistics (Table 6). That is, as participants' scores on the value component were higher, so was the percentage of use of statistics (Table 6). This means that participants who had greater attitudes about the usefulness, relevance, and worth of statistics in personal and professional life were at the same time more likely to use it for a greater proportion of their working time. On the other hand, it has been shown that as participants' scores on the affect component were lower, their percentage of use of statistics was higher (Table 6). That is, participants who had more negative feelings concerning statistics were at the same time more likely to use it for a greater proportion of their working time. However, the standardized beta coefficient was much smaller for affect compared to the value component in the prediction of the percentage of use of statistics.

Table 6

Linear Regression Results Using the Percentage of Use of Statistics as the Criterion

Predictor	***b***	***b* [95% CI]**	***SE***	***beta***	***beta* [95% CI]**	***t***	***p***
(Intercept)	-21.80	[-36.02, -7.59]	7.23			-3.02	.003
Affect	-1.84	[-3.47, -.20]	.83	-.16	[-.30,-.02]	-2.20	.028
Cognitive competence	.75	[-1.60, 3.09]	1.19	.04	[-.08, .16]	.63	.531
Value	6.97	[5.00, 8.94]	1.01	.44	[.32, .56]	6.92	<.001
Difficulty	.74	[-1.26, 2.74]	1.02	.04	[-.07, .15]	.73	.467
Interest	1.03	[-.40, 2.46]	.73	.09	[-.03, .21]	1.42	.157
Effort	-.29	[-1.97, 1.38]	.85	-.02	[-.13, .09]	-.35	.729

Note: b represents unstandardized regression weights; beta indicates the standardized regression weights; CI represents confidence intervals; SE represents the standard error of the estimate; t represents the t-value; p represents the p-value

4. Discussion

This study sought to explore attitudes toward and use of statistics among practicing licensed psychologists in Croatia, providing a full picture of their utilization and recommendations for further improvement of statistical education in psychology. Additionally, it aimed to examine whether these attitudes predicted the use of statistics. Around 20% of the participants stated that they do not use statistics in their work, while others stated that they use it, on average, in 10% of their working time. The most frequently stated reasons for statistics utilization in psychologists' work were conference attendance and publications, sorting and processing the data needed for their work, and creating questionnaires and analyzing the obtained data. Furthermore, the participants' most frequent recommendations were incorporating practical applications and user-friendly software in teaching statistics to improve statistical education in the field. Lastly, the results of this study reveal that attitudes towards statistics significantly predicted the percentage of use of statistics. More specifically, value and affect components of attitudes were found to be significant predictors of the percentage of statistics used in psychologists' working time. It has been shown that those psychologists who placed a greater value on statistics, at the same time were more likely to use it in a greater proportion of their work. On the other hand, the analysis has shown that psychologists who held more negative feelings towards statistics, at the same time were more likely to use statistics more frequently in their work.

The two most frequently stated suggestions for the improvement of statistical education were incorporating practical applications and user-friendly software into teaching statistics. Although practicals exist in most psychology programs' syllabi, it is unclear how well they resemble the real-life problems psychologists may encounter in their work. Practical application, in that sense, means using statistics and teaching statistics in a way that corresponds to real-life situations in which students would need to implement statistics outside of the classroom. This may be achieved by having students conduct their research concerning the material presented during the class, making students combine logic and learning material to practically implement the knowledge obtained, ultimately providing them with needed skills they could use later. The incorporation of real-world applications in statistical education was also noted by Thibault et al. (2024). They emphasized the importance of active learning approaches, such as problem-based learning and collaborative projects, to engage students and improve their understanding of statistical concepts. Also, findings from research conducted by Counsell et al. (2016) suggest that integrating real-world applications and technology significantly enhances students' attitudes and confidence toward learning statistics. Studies have also shown that students who engage in hands-on activities and practical applications tend to have better retention and understanding of the material compared to those who only engage in passive learning activities such as lectures (Prince, 2004). One prominent psychological theory that supports the idea that incorporating practical applications enhances the learning process is the Experiential Learning Theory, proposed by David Kolb (1984.). Kolb emphasizes that learning is most effective when learners have direct experience with the subject matter. Practical applications allow learners to engage actively with the material, making it more relevant and meaningful. The theory also suggests that applying what is learned in practical settings reinforces knowledge and aids in the retention and transfer of learning to new situations. However, the definition of practical application has not been stated in our study, and that remains an open question for future studies. Furthermore, the utilization of user-friendly software was found to be beneficial by numerous researchers (Counsell & Cribbie, 2020; Ditta & Woodward, 2022; TARG Meta-Research Group, 2022). By making statistical tools more accessible, interactive, and supportive, user-friendly software could greatly enhance the learning experience in statistics. It may help bridge the gap between theoretical knowledge and practical application, making the learning process more effective and engaging. Future studies could also investigate the impact of incorporating practical applications and user-friendly software alongside traditional calculations on students' understanding and retention of statistical concepts to gain insight into the efficiency of these techniques and the differences in the outcomes of the two teaching styles.

Additionally, the results of our regression analysis have shown that the value component of attitudes towards statistics significantly predicted the percentage of use of statistics in psychologists' work. More specifically, it has been shown that as the scores on the perceived value of statistics were higher, the use of statistics was more frequent. The relationship between the value and use of statistics means that psychologists who recognize and appreciate the importance and usefulness of statistics are at the same time more likely to use statistics more frequently in their work. On the other hand, it could also be that psychologists who use statistics more frequently are more likely to appreciate statistics value. Although the study design used here cannot give information about the cause and effect of that process, there are several potential explanations for why the relationship between value and frequency of use exists. The Theory of Planned Behavior (TPB), developed by Ajzen in 1985, strongly supports the idea that the value placed on something predicts engaging in the corresponding behavior. One of the key components of TPB is the attitude toward the behavior, which involves the individual's positive or negative evaluation of performing the behavior. This evaluation is closely tied to the values and beliefs the individual holds regarding the outcomes of the behavior. That is, if a person values the outcomes highly, they are more likely to have a positive attitude toward engaging in that behavior. For instance, research has demonstrated that students who place high value on academic success are more likely to engage in behaviors such as studying regularly and participating in class (Eccles & Wigfield, 2002). Their positive attitudes toward these behaviors, influenced by the value they place on educational outcomes, predicted their academic engagement and performance. On the other hand, our findings might also be explained through Cognitive Dissonance Theory (CDT), first proposed by Leon Festinger in 1957, which suggests that when there is an inconsistency between attitudes and behaviors, it creates psychological discomfort (Festinger, 1962). In that sense, CDT explains that psychologists who place a high value on statistics are motivated to use statistical methods more frequently in their work to reduce the psychological discomfort caused by any inconsistency between their values and behaviors. From the CDT perspective, psychologists who need to do statistics more frequently in their work adjust in a way that consequently places a greater value on statistics. This motivation leads to increased engagement with statistical methods, or increased value perception of statistics, aligning their practices with their professional and personal values. Further studies should explore this relationship using a combination of quantitative and qualitative methods, qualitatively assessing psychologists' opinions and experiences with statistics in their work and quantitatively measuring the amount of time spent doing statistics. Based on these findings, it could be potentially beneficial for instructors to stress the importance of statistics in all areas of psychology for students to understand the advantages they gain by possessing adequate statistical knowledge for their future careers. Additionally, promoting a positive perception of the value of statistics could potentially encourage its use within the psychological profession. Furthermore, future studies should implement the aspect of the quality of lecturers in statistics courses and understanding of the content in statistical courses, as these aspects might be important measures for this topic (Verhoeven, 2009).

The regression analysis results also showed that the affect component of attitudes significantly predicted the use of statistics. More specifically, it has been shown that as the scores on the affect component of attitudes towards statistics were lower, the use of statistics was more frequent. The relationship between the affect and use of statistics means that psychologists who hold more negative feelings towards statistics are at the same time more likely to use statistics more frequently in their work. On the other hand, it could also be that psychologists who use statistics more frequently are more likely to develop negative feelings towards it. This finding is quite unusual, not following the theoretical background for the relationship between the affect towards a concept and behavior related to it. For example, it goes contrary to the previously mentioned TPB, which explains that when someone has positive feelings towards a behavior, they are more likely to engage in that behavior. Nevertheless, the found relationship could be described as a form of compensation. Despite negative feelings, psychologists might engage more with tasks related to statistics due to external pressures such as job requirements or academic necessities. On the other hand, it could be that as psychologists are more exposed to statistics and need to perform it more frequently as a part of their job requirements (not their desires), they might develop more negative feelings towards it. Additionally, job demands linked to statistics use usually require advanced technology use and more frequent computer use, which have previously been linked to higher levels of burnout (Kaltenegger et al., 2023), and more negative feelings towards such work (Huang et al., 2015). Future studies could investigate the relationship between burnout and the amount of statistics required from the psychologist to do in their work. These findings could further aid the development of needed intervention strategies to reduce these negative feelings related to statistics in the profession. However, even though the prediction was found to be significant, the beta coefficient of the predictor was rather small (β=-0.16), which has previously been deemed as negligible (Nieminen, 2022). Future studies could further investigate the robustness of the prediction. Identifying whether the prediction is relevant or not could help further develop the theoretical background of the relationship, helping us understand why it exists and how to manage it.

Furthermore, our findings show that, besides theory, most of the time in psychological statistical education is dedicated to hand calculations, and the least amount of time is dedicated to computer use. Conversely, the least number of participants stated that hand calculations were the most important part of statistical education. As noted in the introduction, it has been shown that emphasizing less on hand calculations (and more on software use) could benefit students' learning statistics (Ditta & Woodward, 2022; Pirlot & Hines, 2023). Since there has been a rise recently in the advancement of various statistical software and Artificial Intelligence (AI) tools, this shift might be beneficial considering that these provide students with the automatization of calculations, making calculations easier for them and reducing the need to perform these calculations manually. This allows students to focus more on understanding concepts and interpreting results rather than focusing on computational details. Furthermore, contrary to existing literature that mostly focused on student attitudes (Counsell & Cribbie, 2020;

Dempster & McCorry, 2009; Judi et al., 2011; Landa-Blanco & Cortés-Ramos, 2021; Ramirez et al., 2012), this study extends its view to encompass practicing psychologists, thereby giving insight to the crucial knowledge gap. Our results indicate that psychologists scored the highest among attitude components in terms of cognitive competence and effort, which implies that they think they possess the necessary skills and have made a lot of effort to acquire those skills. On the other hand, the lowest scores were on the difficulty component, meaning that they perceive statistics to be a complex subject to learn. This reflects on the state of statistical education in psychology courses in Croatia, showing that it requires great effort to obtain the needed skills consequently making professionals feel competent to apply those skills later in their work. However, the difficulty of the learning material being perceived as demanding might be due to the statistics course requirements in Croatia. As mentioned previously, the greatest emphasis is placed on theory and hand calculations. This emphasis might contribute to the perceived difficulty of statistics because it involves complex, abstract concepts that are not immediately applicable to practical scenarios. Shifting the focus towards practical application and the use of statistical software could mitigate this by making learning more interactive and relevant, thereby reducing the perceived difficulty and overall negative attitudes towards the course. Future studies could examine how the shift from hand calculations to software use impacts students' comprehension, retention of statistical concepts, engagement, and attitudes toward the course. Additionally, research should assess the effectiveness of instructor training programs in statistical software proficiency and their role in enhancing student learning outcomes.

This study has found that psychologists often use statistics to write research papers and to process and analyze data. The results show that psychologists use statistics for approximately 10% of their working time. Additionally, our results show that around 20% of surveyed psychologists do not use statistics in their work. Since statistics and methodology courses take up to one-third of undergraduate mandatory psychological education in Croatia, it is unknown why there is such an emphasis on statistics in psychological curricula if psychologists rarely use it in their work. Statistical knowledge should be used as an aid for following evidence-based practices and keeping up with relevant research trends. Conducting and reading studies is one of the main advantages of proper statistical knowledge. If psychologists do not use statistics as often, it is questionable whether they follow research trends and read scientific literature. Future studies might examine how improved statistical literacy impacts psychologists' ability to engage with and contribute to current research, and the association between statistical proficiency and the frequency of reading and understanding scientific literature. In our sample, most psychologists report knowledge about statistical utilization, which corresponds to the findings of a study done by Badenes-Ribera et al. (2018), which found that psychologists claim that they have the needed statistical knowledge. On the other hand, their study focused solely on psychologists' knowledge of statistics, without assessing their attitudes towards statistics or patterns of statistics use. Since the findings show that the professionals perceive themselves to be equipped with the needed skills to do statistics, it is unknown why don't they use them in their work. Analyzing the necessity of statistical skills for different areas of psychological practice could be a valuable insight into this topic. Future research could determine if there are specific psychology fields where statistical skills are critical and tailor recommendations accordingly.

This study has several limitations which need to be acknowledged. First, the scale used to measure attitudes towards statistics was initially made for testing students' attitudes towards statistics, and to use it for our sample, we needed to modify it. To do so, we both translated the scale and made it more applicable to our target population. Items were modified in terms of temporal orientation (e.g. "Statistical skills will make me more employable" to "Statistical skills made me more employable") while making sure that we do not change the meaning of the question. However, our reliability scores were similar to those of the previous studies that utilized this scale (Ayebo et al., 2019; Schau et al., 1995; Zhang et al., 2012). Furthermore, the study was conducted entirely online, which limits the interpretation of respondents' identities and whether some of them could complete the questionnaire more than once. Although it may be a general limitation, we minimized this threat by sending emails specifically to licensed psychologists, ensuring we do not reach any other population. Another potential limitation is related to the sample structure. The results have shown that the average of our samples' statistics GPA was 4.0, which is higher than the expected average for the population. This might lead to the overestimation of competence for the general population which might impact the generalizability of the findings. Additionally, the sample contained a few participants who did not finish their degree in Croatia. Regardless, they were included in the analysis, since they are psychologists who work in Croatia and therefore fit the eligibility criteria. Also, they either have a curriculum equivalent to the Croatian one or have had to complete additional coursework to match the Croatian curriculum, therefore, they have the same education as those who finished their degree in Croatia and are not to be excluded.

Furthermore, with the study design being cross-sectional, we are unable to conclude the cause and effect regarding attitudes and the use of statistics. That is, we are unable to determine whether attitudes directly influence the use of statistics, or whether other variables influence this connection, such as self-efficacy and the work environment across different psychological domains. Lastly, the questionnaire was rather large, being composed of a total of 60 questions, which might have induced respondent fatigue and impacted the results. On the other hand, our research was large, with a high response rate (around 31%) and a wide range of data obtained. The study had a comprehensive approach that obtained both quantitative and qualitative data from the sample. Considering their demographic characteristics; participants were predominately female, school, and clinical psychologists, and finished their studies in Croatia. These demographics match the target population, and we collected a sufficient percentage of the population (around 15%). Therefore, to our knowledge, our study is the largest ever conducted on Croatian psychologists. Furthermore, the scale we used gave us a comprehensive examination of statistical attitudes, measuring six different components of attitudes rather than one general measure. Overall, the findings of our study may be used as a cornerstone for making changes in the teaching of statistics in psychology programs.

To conclude, our results underline the need for reform in statistical education within psychology programs, advocating for a curriculum that does not only rely on foundational statistical knowledge but also emphasizes the practical skills relevant to professional practice, as well as the instructors' role in shaping students' attitudes towards the course. Despite the emphasis that is placed on statistics and methodology courses, our results indicate a gap between theoretical understanding and practical application in the field. Practicing psychologists reported using statistics for only a small fraction of their working time, primarily for conference attendance, publications, and data processing. This infrequent use suggests that current educational methods may not emphasize the relevance of statistics to real-life situations for professional contexts. Therefore, examples from actual practice, user-friendly software, and applied activities representing typical challenges that psychologists encounter in their everyday work should be included in curricula. Through statistical education which includes these elements, students could gain more insight and respect for statistics thereby improving their competence and confidence in using statistics. Furthermore, shifting the focus from manual calculations to automated tools and computer programs can allow students to put more emphasis on efficiently interpreting and utilizing statistical data. Nevertheless, as much as this approach is consistent with the growing significance of data-driven decision-making in psychology, it also equips future psychologists with the necessary skills to become more actively involved in research and evidence-based practices, ultimately making their learning experiences directly applicable to their professional careers.

5. Conclusion

This study highlighted a need for reform in statistical education within psychology programs. Despite extensive training, psychologists in Croatia rarely use statistics in their professional work, highlighting the importance of incorporating statistical educational practices that are more linked with the actual work of psychologists. The principal suggested improvements were implementing practical applications and user-friendly software. Additionally, our findings show that higher scores on the value and lower scores on the affect component of attitudes towards statistics were associated with a greater percentage of working time dedicated to statistics use.

6. Abstract

This cross-sectional study investigated the patterns of use and attitudes towards statistics in the everyday work of licensed psychologists in Croatia and gathered their suggestions for improving statistics education in the field. This study aimed to examine if components of attitudes towards statistics predicted the use of statistics in psychologists' work, as well as their suggestions for the improvement of statistical education within psychology programs. It hypothesized that practicing psychologists' use of statistics will be predicted by their attitudes towards statistics and that they will suggest that practical application and user-friendly software would be beneficial for today's psychology students. An online survey was carried out from January to March of 2024. Participants were eligible if they had graduated in psychology, were members of the Croatian Psychological Chamber, and were working in any field of psychology. Invitations were sent using purposive and snowball sampling methods, targeting publicly available email addresses of psychological societies and associations, as well as social media groups that gather psychologists. Additionally, we went through the directory of all licensed psychologists in Croatia (N=3733), collected the publicly available email addresses, and sent the survey invitation to increase the response rate. We collected a wide range of data, and the variables collected could be divided into four categories: demographics, use and knowledge of statistics, recommendations and study experience, and attitudes toward statistics. To analyze the data obtained, we used descriptive statistics and multiple linear regression. We managed to collect a sample of 602 participants, out of which 17 were excluded and 406 completed the whole survey. Psychologists reported using statistics in 10% of their working time, mainly for research papers and data processing while 20% did not use statistics at all. The principal suggested improvements were implementing practical applications and user-friendly software. Additionally, our findings show that a greater perceived value of statistics, and more negative feelings towards statistics were associated with a greater percentage of working time dedicated to statistics use. Despite extensive training, psychologists in Croatia rarely use statistics in their professional work, highlighting the importance of incorporating statistical educational practices that are more linked with the actual work of psychologists. This study, the first to explore the views of Croatian graduated psychologists on the use of statistics in everyday work, provides insights that can inform the design of educational interventions in psychology programs, potentially leading to better alignment between education and professional practice in the psychological field.

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Supplement

Table A

Means and 95% CIs for Each Item and Subscale Score of the SATS-36 Scale (Total N=406)

Factor	No	Description	M [95%CI]
Affect	3	I like statistics.	4.39 [4.22, 4.55]
	4*	I feel insecure when I must do statistics problems	3.77 [3.60, 3.95]
	15*	I would get frustrated going over statistics tests in class.	3.62 [3.45, 3.80]
	18*	I would be stressed during statistics class.	3.80 [3.61, 3.99]
	19	I enjoyed taking statistics courses.	3.57 [3.40, 3.74]
	28*	I am scared by statistics.	2.70 [2.54, 2.86]
Subscale score			**4.34 [4.21, 4.48]**
Cognitive competence	5*	I have trouble understanding statistics because of how I think.	2.38 [2.23, 2.52]
	11*	I had no idea what was going on in the statistics course.	1.80 [1.68, 1.92]
	26*	I make a lot of math errors in statistics.	2.58 [2.46, 2.71]
	31	I can learn statistics.	6.16 [6.06, 6.25]
	32	I understand statistics equations.	4.63 [4.50, 4.76]
	35*	I find it difficult to understand statistical concepts.	2.84 [2.70, 2.99]
Subscale score			**5.53 [5.44, 5.62]**
Value	7*	Statistics is worthless.	1.38 [1.30, 1.46]
	9	Statistics should be a required part of my professional training.	4.98 [4.82, 5.14]
	10	Statistical skills made me more employable.	3.02 [2.82, 3.21]
	13*	Statistics is not useful to the typical professional.	2.29 [2.16, 2.43]
	16*	Statistical thinking is not applicable in my life outside my job.	2.54 [2.39, 2.69]
	17	I use statistics in my everyday life.	3.84 [3.67, 4.01]
	21*	Statistics conclusions are rarely presented in everyday life.	2.86 [2.71, 3.01]
	25*	I had no application for statistics in my profession.	2.49 [2.32, 2.67]
	33*	Statistics is irrelevant in my life.	2.71 [2.55, 2.86]
Subscale score			**5.06 [4.97, 5.16]**
Difficulty	6	Statistics formulas are easy to understand.	3.73 [3.59, 3.87]
	8*	Statistics is a complicated subject.	4.08 [3.92, 4.24]
	22	Statistics is a subject quickly learned by most people.	2.57 [2.46, 2.69]
	24*	Learning statistics requires a great deal of discipline.	4.76 [4.62, 4.90]
	30*	Statistics involves massive computations.	3.49 [3.35, 3.64]
	34*	Statistics is highly technical.	3.96 [3.82, 4.10]
	36*	Most people must learn a new way of thinking to do statistics.	4.06 [3.91, 4.21]
Subscale score			**3.71 [3.63, 3.79]**
Interest	12	I am interested in being able to communicate statistical information to others.	3.97 [3.78, 4.15]
	20	I am interested in using statistics.	5.04 [4.89, 5.20]
	23	I am interested in understanding statistical information.	5.34 [5.20, 5.48]
	29	I am interested in learning statistics.	4.52 [4.34, 4.69]
Subscale score			**4.72 [4.58, 4.86]**
Effort	1	I tried to complete all my statistics assignments.	5.93 [5.82, 6.04]
	2	I worked hard in my statistics courses.	5.50 [5.36, 5.63]
	14	I tried to study hard for every statistics test.	5.83 [5.70, 5.95]
	27	I tried to attend every statistics class session.	6.26 [6.15, 6.36]
Subscale score			**5.88 [5.79, 5.97]**

Figure A

Flowchart of Participants in the Study

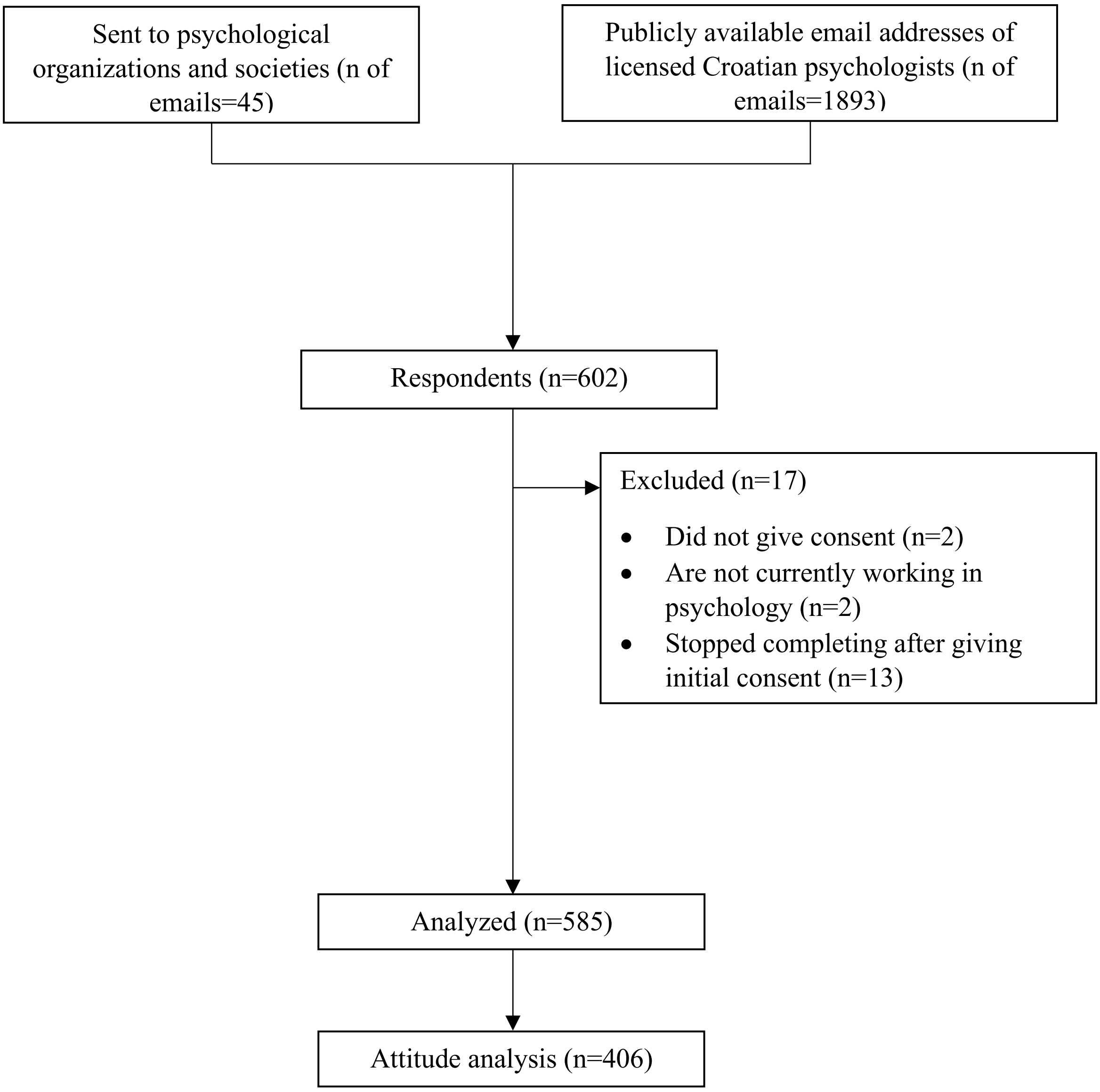
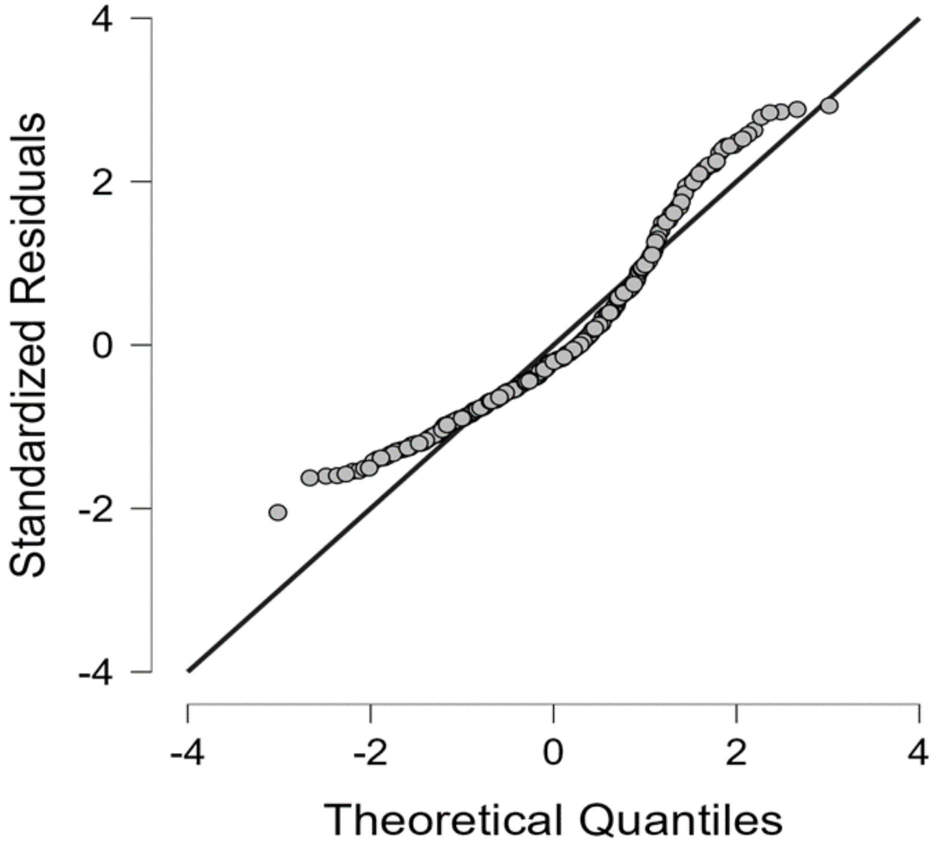


Figure B

Q-Q Plot of Standardized Residuals



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Student/ica: NIKA VUCO

Naslov rada: PATTERNS OF USE AND ATTITUDES TOWARDS STATISTICS IN PSYCHOLOGICAL PROFESSION

Znanstveno područje i polje: SOCIAL SCIENCES - PSYCHOLOGY

Vrsta rada: FINAL THESIS

Mentor/ica rada (ime i prezime, akad. stupanj i zvanje):
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LANA PEHAR, mag.

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