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Two Aspects of Bias in Multivariate Studies: Mixing Specific with General Concepts and “Comparing Apples and Oranges”

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A B S T R A C T

This paper presents two types of bias that occur relatively often when using multivariate analysis. For both types of bias, it is characteristic that the number and choice of different types of variables are not balanced by application of clear methodological rules. Following the interpretation of broader theoretical positions, which include "confirmation bias" (of initial hypothesis) and "misspecification bias", a description of two types of bias characteristic of multivariate analysis are given: "mixed-level bias" (in terms of specificity - generality) and "mixed-constructs bias" . Both types of bias further enhance the disparity in the number and ratio of different types of variables in the same multivariate analysis. Details of situations, when these two types of bias appear, are presented and displayed in four different examples. Several strategies are proposed as to how these types of bias can try to be avoided, during the preparation of studies, during the statistical analyses and their interpretation.

Key words: *Mixed-constructs bias, Mixed-level bias, Multivariate analysis.*

Introduction

This article is about two not so sporadic events in scientific publications, which have the same consequence: using multivariate statistical methods for getting (consciously or unconsciously) biased final findings. For both types of events, it is characteristic that the number and choice of different types of variables in research is not balanced by applying clear methodological rules.

In these cases, the ‘usual’ mistakes during performing research process, such as ‘seven statistical deadly sins’ are not done: (1) the use of parametric analysis of ordinal data; (2) the inappropriate use of parametric analysis in general; (3) the failure to consider the possibility of committing type II statistical error; (4) the use of unmodified t-tests for multiple comparisons; (5) the failure to employ analysis of covariance, multivariate regression, nonlinear regression, and logistical regression when indicated; (6) the habit of reporting standard error instead of standard deviation; (7) the underuse or overuse of statistical consultation[1]. These types of bias also do not appear because of the use of invalid statistical methods, or invalid grouping of cases, or invalid grouping of indicators. For example, if more than one factor is related to the outcome and factors are even interdependent, more complex statistical tests like regression analyses are required. Also, the grouping of too many different cases sets an undeterminable bias and is therefore not acceptable. Finally, indicators which are too simple can miss the main point of the construct that has to be represented[2]. Frequently, practitioners seek to use categorical data in the course of model building using simple and multiple linear regression analysis[3]. However, it is incorrect to recode such variables using numeric values to be included in regression analysis[3], while the ‘dummy’ variables are exceptions from this rule. However, all these mistakes can be avoided through correct use of multivariate and univariate statistics[4].

When analyzing the sources of two events, mixing specific with general concepts and “comparing apples and oranges”, the first step is considering the consequences of these specific mistakes while performing multivariate analyses. This leads us to the concepts of confirmation bias and misspecification bias.

Confirmation Bias

Confirmation bias (confirmatory bias, myside bias) is an inclination of people to favor information that confirms their beliefs or hypotheses. People tend to gather or remember information selectively, or interpret it in a biased way[5]: the effect is stronger at emotionally charged issues and for deeply entrenched beliefs. Confirmation biased researchers also tend to interpret ambiguous evidence as supporting their existing position, in few aspects: hypothesis-determined information seeking and interpretation, restriction of attention to a favored hypothesis, preferential treatment of evidence supporting existing beliefs, looking only or primarily for positive cases, overweighting positive confirmatory instances, seeing what one is looking for[5]. The confirmation bias in real-world contexts leads to the explanations of the confirmation bias, with the following motives: the desire to believe, information-processing bases for confirmation bias, positive-test strategy or positivity bias, conditional reference frames, pragmatism and error avoidance, and educational effects[5]. There are numerous examples of confirmation bias in many fields of scientific research[6]. For example, when making questions in some questionnaire, certain positive dimensions could be weighted more heavily in choosing than in rejecting, while negative dimensions might be weighted more heavily in rejecting than in choosing: the enriched option tends to be chosen and rejected relatively more often than the impoverished option, what

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could be extended to nonbinary decision problems[7]. The second example describes field listing of housing units, as an expensive and time-consuming stage of the survey process. Using an experimental repeated listing design to demonstrate the presence of confirmation bias in dependent listing, the evidence is found that when provided with an initial listing to update in the field, listers can become too trusting of the list: they tend not to add missing units or delete inappropriate units[8]. Third research is about auditors, who have confirmatory bias towards the findings of the prior year audit opinion and the consequences for consistency in auditor reporting behaviour. There is a lack of consistency in audit reporting behaviour, particularly with regard to the liquidity position of the firms. The lack of consistency is associated with firms that switched auditors after receiving a first time going concern modification[9]. Fourth, academic psychologists show a tendency to rate the quality and appropriateness of scientific studies more favorably when results and conclusions are 'in line' with their own prior beliefs. Psychologists tended to evaluate results significantly higher when they conformed to their own prior expectations, for example, when astrological hypotheses were disconfirmed[10]. Fifth, thought processes of people can have a significant impact on software quality: on the way software is designed, developed and tested by people. Patterned deviations of human thought from the laws of logic and mathematics (cognitive biases) are a likely cause of software defects[11].

Misspecification bias

So-called 'misspecification bias' can be met in numerous contexts of multivariate analyses. Most of the examples come from multiple regression analyses, factor analyses and structural equations modeling. Here are presented some of these examples, together with recommendations for avoiding this type of bias.

Researchers in a number of disciplines have argued that much of past research may have incorrectly specified the relationship between latent variables and indicators as reflective when an understanding of a construct and its measures indicates that a formative specification would have been warranted[12]. Also, the posited severe biasing effects of construct misspecification on structural parameters in ***structural equations modelling***, lead to concluding that an important portion of the literature is largely invalid: but construct misspecification, in general does not lead to severely biased estimates[12]. The other opinion is the belief that regardless of the extent of the bias, it is critically important for researchers to achieve correspondence between the measurement specification and the conceptual meaning of the construct so as to not alter the theoretical meaning of the construct at the operational layer of the model[13]. This alignment between theory and measurement will safeguard against threats to construct and statistical conclusion validity[13]. A proper model is fully supported by the data and has enough parameters to avoid bias, but not too many that precision is lost: it is the Principle of Parsimony[14]. Classical model selection has been based on goodness-of-fit tests, which test only against general alternative hypotheses. The alternative is between-model tests, a likelihood ratio test with a specific alternative hypothesis[14]. Model selection based on classical hypothesis testing can be very difficult and has unknown properties: Akaike's Information Criterion (AIC), likelihood, quasilikelihood, and data resampling, provide modern methods to achieve valid inference[14].

Model misspecification in regression has long been a well-recognized research problem and the estimation biases resulting from a misspecified model can be very serious[15]. In one numerical example, a classic simple or ***multiple linear regression*** can achieve with 0.99 probability a near perfect fit to a random sample of any size but due to the omission of an independent variable the signs of the estimated coefficients are all wrong, thus distinguishing prediction from causation[15]. Multiple regression with $R^2 \approx 1$ is a criterion for correct model specification, but even a multiple regression with the best inferential statistics is no guarantee for being a correct model[15]. The bias induced by these "unobserved" variables in linear regression equations is called the unobserved variables bias[16].

The appropriate measure of ***inflation uncertainty*** is relative measure to the gross expected rate of inflation[17]. Empirical studies of the effects of inflation uncertainty have misspecified their models by not using the relative measure: the bias is equivalent to omitting a relevant variable. It is necessary to use the relative measure in future studies of this issue[17].

The debate about ***propensity score*** is concerned with the number of pre-treatment variables that should be included in the propensity score. The standard practice when estimating a treatment effect is to include all available pre-treatment variables, but this approach is not always optimal, when the goal is bias reduction[18]. Including an additional relevant variable in the propensity score can increase or decrease the bias on the effect of interest. However, the balance tests and sensitivity analysis provide limited protection against overadjustment.[18]

Factor analysis is a technique which is designed to reveal whether or not the pattern of responses on a number of tests can be explained by a smaller number of underlying traits or factors. Similarly, there are many ways it can be abused and misinterpreted[19]. The posterior probabilities ***in latent class analysis*** (LCA) are generated using a non-inclusive LCA that includes manifest indicators, but not other variables of interest that are included in the analysis model[20]. When the analysis model is more general than the classification model, it is expected that the estimated relations between latent class membership and the other variables are attenuated: the use of an inclusive LCA, in which all variables included in the analysis model are also included in the classification model, is proposed[20].

Mixed Levels Bias and Mixed Types Bias

Selection of an appropriate model as the basis for data analysis is critical for valid inference: the data will only 'support' limited inference[14]. A model should have enough structure and parameters to account adequately for the significant variability in the data, but in the cases when the model has too much structure or too many parameters, precision is unnecessarily lost and 'effects' may be inferred that are not justified by the data[14]. The absence of a clear rule as to which extent data analysis has to be leaded by data or theoretical model, could be addressed as a source of two types of bias, suggested by the author of this article.

Namely, researcher's choice determines the decision regarding which different **types** of variables will be included in multivariate research, as well as a **number** of variables which are included in multivariate research design.

First type of events, mixing general (latent variable) concepts with specific (manifest) variables in the same multivariate analysis could be called *'mixed levels bias'*. While choosing variables, whether based on the previous findings or spontaneously, researcher could analyse simultaneously the variables with different levels of the specificity. For example, factor scores for the sets of variables that represent, say, instrumental aggressiveness (which comprise 50 manifest variables), together with numerous sets of single manifest variables which represent a variety of individual's behaviours in specific life situations. Both types of variables could be used in the same analysis (for example, linear multiple regression, canonical discrimination or factor analysis)

Second type of events, called 'comparing apples and oranges', describe the situation when in the same multivariate analysis (especially in the situation when 'mixed levels bias' is not controlled) different types of variables are used: biological, psychological, kinesiological, economical, etc.). This source of bias could be called '***mixed constructs bias'***. For example, the researcher could choose just three variables which represent some psychological constructs in kinesiology and, say, 25 indicators of health status, performing some method of multivariate analysis: psychological variables would have a small chance appearing statistically significant, or to form strong founded latent variable, as compared with variables which describe the space of health status.

Examples of two types of bias

In one simple study about the attitudes of swimming coaches in Croatia, both of the abovementioned types of bias are illustrated. The study included 71 swimming coach, 44 of which were male and 27 female, from the majority of Croatian swimming clubs (23 in total), from Zagreb, Varaždin, Tuhelj, Sisak, Osijek, Pula, Poreč, Rovinj, Rijeka, Šibenik, Split, Dubrovnik and Korčula. The study was conducted on a sample of swimming coaches, with different age, length of service, qualifications and age categories of swimmers with which he/she works.

Among standardized psychological instruments, Croatian version of Burn's Perfectionism Scale is used, which measures one-dimensional perfectionism, which describes generalized but negative perfectionism[21]. It contains 10 items, to which the subjects reply on a Likert type 5-point scale, the greater estimate meaning greater agreement with content of the statement. In the study of perfectionism in basketball players, two types of 'unidimensional' perfectionism revealed: manifest (obvious in behavior) and experiential perfectionism[22]. Motive of achievement is measured on the scale MOP2002[23]: this scale of achievement motives was Likert's type of 5 degrees, with 55 items. Four factors of the scale MOP2002 (four dimensions of achievement) are comprised in this research in only one general score.

A few sets of variables are derived from the items of the **Questionnaire for swimming coaches**. The first set of variables were **general** (mostly demographical) variables, defined as follows: gender, age, education level, marital status (all nominal variables except age). Second set considered variables ***directly related to swimming***: work experience as a coach, duration of swimming experience, chronological age in which the swimmer stopped swimming, number of swimmers with whom he/she works as a coach (all the ratio variables), previous engagement in competitive swimming, holding medals from national championships, membership in some of the national selections in swimming (cadet, junior and senior), reasons for the cessation of active engagement in swimming (own will, sports injuries or disease, disagreeing with the club, disagreements with other coaches, critical life events, greater ambitions than the possibility of the club), a permanent working contract in the club, age category of swimmers with whom he/she works (swimming school – young children, cadets, juniors and seniors) (all the binary variables). The third set of variables that indicate ***attitudes towards job and coaching in the club***: job satisfaction, satisfaction with monthly income at the club, satisfaction with the schedule of activities at the club, potential to make a better schedule of activities at the club, the maintenance of professional meetings, the flow of information, stimulating relationships, board members are working for the good of the swimming, swimmers appreciate coach's work, the exploitation of the government and swimmers (three-point estimation scale for all the variables). Variables that indicate ***attitudes toward coaching swimmers***: the existence of non-perspective swimmers, preference to work with a decent swimmer who is not perspective, whether it is working with unpromising swimmer demotivating, involvement in working with unpromising swimmers, willingness to invest the efforts in unprofitable swimmers, preference to work with a swimmer inappropriate behavior but promising, whether seniors quit swimming if they do not win medals at state championships (three-point estimation scale for all the variables). Variables that indicate ***attitudes toward coaching their own child*** as a future swimmer: the inclusion of their own child in swimming, personal training of the child. Respondents who have children did not respond to these two questions (both binary variables). Variables that indicate ***the perceptions of the 'high quality' coach***: can someone be a good coach who is not engaged in swimming, can someone be a good coach without proper school (both three-point estimation scales). One variable is about ***self-assessment of their own work***: how good I am doing my job as a coach (three-point estimation scale). The last set consists of variables that indicate ***attitudes toward fellow coaches and competition system***: his/her colleagues are doing their job well, the system of competition is stimulating for the development of swimmers (three-level estimation scale).

Example 1: Mixed levels bias in canonical discrimination analysis

In the first two examples, the main goal is to determine the factors of differences for attitudes about swimming coaching, together with two psychological characteristics, with different choices of variables.

In the first example, three latent variables are chosen (two types of perfectionism and composite score in achievement motivation), together with a few single (manifest) variables (all other variables about swimming coaching) (Table 1). In spite of the fact that in general the discrimination function does not show the difference between female and male coaches, in one single variable (whether someone without proper education can be a good coach) the difference is found (higher mean value for female coaches). However, it has to be mentioned that experimental and manifest perfectionism comprise the data from 10 single items, while the score in achievement motivation comprises the data from 55 items in total. Simple consideration leads to a hypothesis that more general and complex latent psychological variables are in the same range with single manifest variables in discriminant analysis. On the other hand, the number of complex vartiables is less than the number of manifest variables, which can have higher likelihood to appear statistically significant.

TABLE 1
DISCRIMINATION ANAYLSIS AMONG THE COACHES THAT BELONG TO DIFFERENT GENDER IN A SET OF VARIABLES ABOUT SWIMMING COACHING

Discrimination Function	**Eignevalue**	**Wilks's λ**	***Canonical correlation***	χ^2-test (degrees of freedom)
	0.177	0.850	0.388	10.597

Variables	Wilks's λ	Correlation with discriminational factor	F-test (1,69)	**Mean** males	**Mean** females	**σ** males	**σ** females
experiental perfectionism	1.000	0.001	0.001	10.614	10.667	4.088	9.348
manifest perfectionism	0.999	-0.068	0.056	16.250	16.111	2.441	2.326
achievement motivation	0.995	0.168	0.345	242.409	246.296	29.120	23.294
can be a good coach someone who is not engaged in swimming	1.000	-0.033	0.013	2.500	2.481	0.629	0.700
can be a good coach someone without proper school	0.913	0.734	**6.587***	1.864	2.296	0.734	0.609
I prefer to work with a decent swimmer who is not perspective	0.963	0.465	2.643	1.432	1.630	0.501	0.492
whether it is working with unpromising swimmer demotivating	0.996	0.009	0.275	1.432	1.519	0.695	0.643
job satisfaction	0.959	-0.491	2.947	2.750	2.519	0.488	0.643
		Centroids		-0.325	0.530		

Legend: * test significant at p< .05 level; Bold – names of complex (more general) variables

TABLE 2
DISCRIMINATION ANAYLSIS AMONG THE COACHES THAT BELONG TO DIFFERENT GENDER IN A SET OF VARIABLES ABOUT SWIMMING COACHING

Discrimination Function	**Eignevalue**	Wilks's λ	***Canonical correlation***	χ^2-test (degrees of freedom)
	0.341	0.746	0.504	**18.786***

Variables	Wilks's λ	Correlation with discriminational factor	F-test (1,69)	**Mean** males	**Mean** females	**σ** males	**σ** females
achievement motivation	0.995	-0.121	0.345	242.409	246.296	29.120	23.294
unidimensional perfectionism	1.000	0.010	0.002	26.864	26.778	5.192	10.237
job satisfaction	0.959	0.354	2.947	2.750	2.519	0.488	0.643
satisfaction with income	0.997	0.096	0.217	1.977	1.889	0.821	0.698
satisfaction with the assignment of tasks in the club	0.841	0.744	**13.034****	2.409	1.778	0.757	0.641
board members are working for the benefit of swimming	0.940	0.432	4.393	2.250	1.852	0.781	0.770
swimmers appreciate my work	0.985	-0.209	1.027	2.750	2.852	0.438	0.362
exploitation by management and swimmers	0.999	-0.053	0.066	1.477	1.519	0.698	0.580
stimulating relationships	0.846	0.729	**12.515****	2.432	1.778	0.695	0.847
the flow of vocational information	0.922	0.499	**5.859***	2.068	1.519	0.974	0.849
		Centroids		0.451	-0.735		

Legend: *significant at p< .05 level; **significant at p< .01 level; Bold – names of psychological complex variables

Example 2: Mixed constructs bias in canonical discrimination analysis

In the second example, two latent variables are chosen (unidimensional perfectionism and composite score in achievement motivation), together with a few single (manifest) variables (all other variables about swimming coaching) (Table 2). In this case the discrimination function shows statistically significant difference among female and male coaches, as well as in three single variables (satisfaction with the assignment of tasks in the club; stimulating relationships in the club; the flow of vocational information) the difference is found (in all tree cases, higher mean values are found for male coaches). In this case also it has to be mentioned that unidimensional perfectionism comprises the data from 10 single items, while the score in achievement motivation comprises the data from 55 items in total (this can be also the example for mixed levels bias, too), while the other variables are single manifest ones. Specific consideration here is directed to the fact that all variables in this function comprise very different number of variables that belong to different concepts: psychological characteristics, attitudes towards job and coaching in the club, perceptions of the 'high quality' coach, attitudes toward fellow coaches and competition system. The hypothesis about *mixed constructs bias* appears from the fact that different number of variables from different thematic issues (and/or constructs) of the questionnaire is included in the same discriminant analysis. Hence, variables from more numerous represented thematic issues (and/or constructs) can have a higher likelihood of appearing statistically significant.

Example 3: Two types of bias in principal components analysis (PCA)

In the third example, the main goal is to determine the latent structure of attitudes about swimming coaching, together with two psychological characteristics. Principal Component Analysis (PCA) with Varimax rotation was performed (Table 3). In this case, a different number of variables from different thematic issues (and/or constructs) of the questionnaire is included in the same PCA. The fact that three latent variables are chosen (two types of perfectionism and composite score in achievement motivation), together with a few single (manifest) variables (all other variables about swimming coaching) in the same PCA, indicate previously described *mixed level bias*. The hypothesis about *mixed constructs bias* ('comparing apples and oranges') appears from the fact that a different number of variables from different thematic issues issues (and/or constructs) of the questionnaire is included in the same PCA. Hence, variables from more numerous represented thematic issues (and/or constructs) can have higher likelihood of satisfactorily saturating the principal components (PC). PCA of these mixed constructs with different level of the specificity, produced relatively 'explainable' PCs, but only psychological characteristics form one clear PC, while the other two are suspect. In case when we omit some variables in the second iteration of PCA, to remove variables with suspect interpretability, it will lower the reliability of the PC.

TABLE 3
PRINCIPAL COMPONENTS ANALYSIS WITH VARIMAX ROTATION FOR THE COACHES IN A SET OF VARIABLES ABOUT SWIMMING COACHING

Items	**Experience**	**Job characteristics**	**Psychological characteristics**
years of work experience	**0.880**		
age	**0.825**		
personal coaching own child	**-0.688**		
can be a good coach someone without proper school	**0.502**		
can be a good coach someone who wasn't swimmer		**-0.694**	
job satisfaction		**0.689**	
years of engagement in swimming		**0.687**	
satisfaction with the assignment of tasks in the club	0.335	**0.554**	
satisfaction with income		**0.488**	0.423
achievement motivation			**0.863**
manifest perfectionism		-0.320	**0.748**
experiential perfectionism			**0.627**
Eigenvalue	**2.375**	**2.157**	**2.032**
Variance Explained (%)	**19.79**	**17.97**	**54.70**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.494	**Bartlett's Test**	107.992**

Legend: *significant at p< .05 level; **significant at p< .01 level; Bold – names of psychological complex variables, together with satisfactory saturations for principal components

Example 4: Two types of bias in linear multiple regression analysis

In the fourth example, the main goal is to use a set of variables (attitudes about swimming coaching, together with one psychological characteristic) to predict self-perceived quality of coach's work. This example deals with linear multiple regression analysis (MRA) (Table 4). In this case, a different number of variables from different thematic issues issues (and/or constructs) of the questionnaire is included in the same MRA. The fact that three latent variables are chosen again (two types of perfectionism and composite score in achievement motivation), together with a few single (manifest) variables (all other variables about swimming coaching) in the same MRA, indicate previously described *mixed level bias*. The *mixed constructs bias* appears from an uncontrollably different number of variables from different thematic issues (and/or constructs), included in the same MRA. Hence, variables from more numerous represented thematic issues (and/or constructs) can have a higher likelihood of appearing as statistically significant predictors in MRA. MRA that use these mixed constructs with a different level of the specificity, produced statistically insignificant R-coefficient, but with some significant single predictors: age, achievement motivation and the existence of nonperspective swimmers.

TABLE 4
MULTIPLE REGRESSION ANALYSIS: FORECASTING THE PERCEIVED QUALITY OF COACHING JOB ON THE BASE OF PREDICTORS - SET OF VARIABLES ABOUT SWIMMING COACHING

Predictors	**Beta**	**t**	**p (t)**
job satisfaction	-0.068	-0.388	0.701
satisfaction with income	-0.084	-0.505	0.616
age	0.329	2.127	**0.040**
achievement motivation	0.407	2.059	**0.047**
the existence of nonperspective swimmers	0.329	2.185	**0.035**
disagreement with coaches	-0.093	-0.625	0.536
experiential perfectionism	-0.226	-1.403	0.169
manifest perfectionism	-0.183	-1.032	0.309
swimmers appreciate my work	-0.103	-0.681	0.500
whether it is working with unpromising swimmer demotivating	-0.163	-0.972	0.338
Criterion - how good I'm doing my job as a coach	**R=0.550** R^2=0.303; F (10,36)=1.562		

Legend: *significant at p< .05 level; **significant at p< .01 level; Bold - psychological complex variables

Conclusion and recommendations

While describing misspecification bias, many strategies how to reduce specific types of misspecification bias in specific types of data analyses, were suggested. For these simple types of bias *(mixed level bias* and *mixed constructs bias),* two general strategies could be suggested. Firstly, to avoid *mixed level bias,* the researcher has to decide if he/she wants to analyze latent (complex) variables or manifest (single) variables: separate analyses have to be done for latent variables and separate analyses for manifest variables. Secondly, to avoid *mixed constructs bias,* the researcher first has to analyze one set of the variables (manifest or latent) separately (which describe some specific thematic issue), while after performing data analyses in that step, the same levels of variables (manifest or latent) in these thematic issues can be directly analyzed in the next step of multivariate analyses. However, the bias induced by 'unobserved' variables (not only in the linear regression equations) or unobserved variables bias[16, 24], cannot be avoided, except through the continuous progression of the scientific knowledge in certain scientific fields (which can enable including new relevant variables in studies), together with honesty and high ethics of the researchers.

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DVIJE VRSTE PRISTRASNOSTI U MULTIVARIJATNIM STUDIJAMA: „PRISTRASNOST POMIJEŠANIH NIVOA" I „PRISTRASNOST POMIJEŠANIH KONSTRUKATA"

S A Ž E T A K

U članku su predstavljene dvije vrste pristrasnosti koje razmjerno često nastaju pri korišćenju multivarijatnih analiza. Za obije vrste pristrasnosti, karakteristično je da broj i odabir različitih tipova varijabli nisu uravnoteženi primjenom jasnih metodoloških pravila. Nakon tumačenja širih teorijskih polazišta, koja obuhvataju "pristrasnost potvrđivanja" (inicijalnih hipoteza) i "pristrasnost nedostatka specifikacije", dat je opis dvije vrste pristrasnosti karakterističnih za multivarijatne analize: "pristrasnost pomiješanih nivoa"(specifičnosti-uopštenost), te "pristrasnost pomiješanih konstrukata". Obije vrste pristrasnosti dodatno pojačava nesrazmjernost u broju i omjeru različitih tipova varijabli u istoj multivarijatnoj analizi. Pojedinosti o situacijama pojavljivanja dvije predstavljene vrste pristrasnosti su prikazane na četiri različita primjera. Predložene su strategije kako se navedene vrste pristranosti mogu pokušati izbjeći, tokom pripreme istraživanja, ali i tokom statističkih analiza i njihove interpretacije.

Ključne riječi: pristrasnost pomiješanih konstrukata, pristrasnost pomiješanih nivoa, multivarijatna analiza.