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MITIGATING CENTRAL TENDENCY AND ACQUIESCENCE BIASES IN SURVEY DESIGN: A METHODOLOGICAL EXPLORATION WITH EMPIRICAL EVIDENCE

This paper presents a survey design methodology aimed at mitigating central tendency and acquiescence biases, which are commonly encountered in traditional Likert-scale surveys. The proposed approach employs a forced ranking method, using a case study involving 220 engineering students at the University of Zagreb as a source of data to assess whether respondents exhibit patterns of systematically avoiding honest answers for any reason. Statistical analysis demonstrates the effectiveness of the design in reducing these biases. The results provide strong evidence that the method developed in this article can minimize response distortions without sacrificing data richness. While the primary focus is on the methodological aspects, the case study illustrates the potential of this approach for ethical and attitudinal research. The study concludes with recommendations for refining survey techniques and exploring their broader applicability in different populations and contexts.

Keywords: central tendency, acquiescence bias, Likert scale, student attitudes, ethics

INTRODUCTION

Likert scales (Likert, 1932) are used to measure people's attitudes, opinions, or perceptions by asking them to rate their level of agreement or disagreement with a series of statements on a multi-point scale, typically ranging from strongly agree to strongly disagree. They are widely utilized in social science research due to their simplicity and effectiveness in capturing subjective data, making them crucial for quantitative analysis in fields like psychology,

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sociology, and education. However, Likert scales can present methodological challenges, such as central tendency bias (where respondents prefer the most neutral rating), acquiescence bias (tendency to agree with statements), and difficulties in ensuring that equal intervals between points reflect true differences in attitudes, which can affect the accuracy of data interpretation.

In this article, we discuss the design of a Likert scale-based survey that aims to avoid the problem of central tendency and test it in the specific context of obtaining students' ethical attitudes in the areas of business and academic conduct. The utility of Likert scales in survey research is well-documented. Willits et al. (2016) provide an in-depth examination of the theoretical foundations of Likert scales, highlighting their prevalence in social sciences.

Several studies address the common challenges and misuses of Likert scales. Bishop and Herron (2015) and Pornel and Saldana (2013) critique the improper treatment of ordinal data as interval data, which can lead to erroneous conclusions. Similarly, Mircioiu and Atkinson (2017) compare parametric and non-parametric methods applied to Likert data, underscoring the potential pitfalls in data interpretation when assumptions about data distribution are ignored. Parker et al. (2019) further investigate whether research participants provide interval or ordinal responses when using Likert scales, highlighting the ambiguities in respondent interpretation.

Recent advancements in scale development are captured in the works of Jebb et al. (2021) and Kreitchmann et al. (2019), who explore new approaches for mitigating response biases and improving the psychometric properties of Likert scales. Kreitchmann et al. (2019) advocate for forced-choice formats and psychometric modeling as superior methods for controlling response biases, contrasting them with traditional Likert scales.

Concerns regarding the reliability and validity of Likert scales are central to the studies by Joshi et al. (2015) and Louangrath (2018). Both studies argue that while Likert scales are valuable tools for measuring attitudes and perceptions, their effectiveness is contingent on rigorous design and validation procedures. The issues of reliability, validity, and potential biases are further explored by Kusmaryono et al. (2022), who conduct a comprehensive review of response options in Likert-scale research.

Several studies offer methodological guidance for enhancing the robustness of Likert-scale research. Allen and Seaman (2007) provide practical recommendations for data analysis, cautioning against the oversimplification of complex data sets.

The integration of advanced statistical models, such as the Rasch model, a mathematical model used in psychometrics for analyzing data from assessments, surveys, or questionnaires to measure latent traits (unobservable characteristics like ability, attitude, or personality), is explored in studies by Andrich (2005), Retief et al. (2013), and von Davier (2016). These studies highlight the advantages of using the Rasch model for refining Likert-scale instruments, offering a more sophisticated approach to understanding underlying latent traits and enhancing the precision of measurement tools. Wu and Adams (2007) discuss the application of the Rasch model in psycho-social measurement, offering practical approaches for enhancing scale utility. This is complemented by Nemoto and Beglar (2014), who discuss the practical aspects of developing Likert-scale questionnaires, emphasizing the importance of precise wording and scale construction to minimize bias and enhance reliability. Tanujaya et al. (2023) discuss the difficulties and challenges encountered in social sciences research when using Likert scales, advocating for more robust statistical models.

The reviewed literature points to several future directions for research. McLeod et al. (2011) suggest revisiting traditional Likert scale approaches to incorporate new methodologies that may better capture nuanced respondent attitudes. Tanujaya et al. (2023) call for a deeper exploration of cultural and contextual factors that influence survey responses, advocating for the development of more culturally sensitive instruments.

In this paper, we want to append to our previous preliminary research (Sabolic et al., 2022) that examined methodological considerations specific to educational research, proposing strategies to mitigate central tendency bias and improve the accuracy of student attitude assessments.

CENTRAL TENDENCY AND ACQUIESCENCE BIASES

If central tendency and/or acquiescence biases are particularly prominent, concerns are raised about the reliability of the responses provided by participants. In a sense, these two biases can be viewed as related phenomena, differing primarily in their position along the Likert scale, but driven by similar underlying psychological causes.

Several factors may contribute to the inadequacy of information gathered through Likert-scale surveys, as already discussed in Sabolic et al. (2022). Central tendency is likely a consequence of a conscious or subconscious desire to avoid providing a definitive answer, which may be driven by various reasons. Some of these reasons, based on our experiences as educators and as respondents, will be discussed below. It often stems from a desire to quickly complete a survey in which the respondent has little intellectual engagement, simply to fulfill an obligation, a promise, or something similar. On the other hand, more serious reasons are also possible, such as fear of expressing true opinions.

Nevertheless, some respondents who choose a neutral answer genuinely hold a neutral position. The issue is that they are indistinguishable from respondents who select the middle option without expressing their true type. If the survey itself is poorly designed (regardless of the Likert scale variation or any other form of attitude collection used), the problem of central tendency is likely to be much more pronounced than usual, potentially to the extent that the survey results provide almost no meaningful conclusions.

Acquiescence bias, in our opinion, arises for reasons that are, in many cases, similar to those that lead to central tendency. For instance, if one of the response options is obviously the most "socially acceptable" and thus the "least risky," while the others are not, it is highly likely that the majority of respondents will select that option, even if it is not in the middle of the Likert scale. For example, if participants are asked to express their agreement with the statement, "I think it is acceptable to embezzle money from the company I manage if it does not significantly impact its long-term financial interests," almost everyone in their right mind would choose "Strongly Disagree" even if, in reality, they may hold an opposing view. Such a survey question formulation cannot provide any meaningful insight into the attitudes of the surveyed group.

This example illustrates our primary motivation to modify the survey procedure, which we will describe and test in the following sections.

If survey participants are unsure of their anonymity, they may sometimes fear giving an honest answer due to potential consequences. If anonymity is not guaranteed or is difficult to ensure, respondents may avoid revealing their true type. For example, if students do not believe in anonymity for any reason (real or imagined), many will avoid giving negative feedback about the quality of their professors' lectures. Similarly, many employees may refrain from expressing their true opinions about the morality or competence of their managers. Moreover, respondents who are uncertain about what the "correct answer" is (i.e., the one least risky for them) may often choose the neutral option when in doubt.

Prevailing social and cultural norms can also influence the completion of survey questionnaires. In some societies, there is a strong culture of politeness, non-confrontation, and conflict avoidance. The belief in the "wisdom of the masses," that a balanced position is the most socially desirable, falls into the same category of reasons for central tendency bias.

A poorly designed survey, where it is perceived or implied that the survey author underestimates the intelligence of the surveyed population or that the author may be incompetent in the subject matter, often leads to respondents seeing no purpose in participating in the survey and simply choosing the easiest solution: the neutral option for almost every question.

Another potentially important reason for choosing a neutral response, as we observed in previous research (Samuelson et al., 2022), is the inherent limitation of the Likert scale, which offers only a small number of possible responses that cannot capture the full continuum of someone's ideas or preferences. Increasing the number of options on a Likert scale or even introducing a more modern analog continuous method of response selection, as discussed in Matejka et al. (2016) and Buskirk et al. (2015), does not necessarily guarantee compatibility with an individual's internal system of ideas and reasoning. While the distribution of responses may appear more continuous at first glance, the correspondence between these responses and the true ideas in the respondents' minds is questionable.

Finally, one of the significant reasons for the occurrence of central tendency and, occasionally, acquiescence bias is the lack of motivation among the surveyed population. For example, if students are required to engage in a significant and time-consuming activity which does not contribute to their course grade, such as filling out a long survey, they have no incentive to participate constructively. In such cases, the easiest choice is to select the middle option for every question.

Douven (2017) provides a Bayesian perspective on the issue of central tendency, arguing that it represents a natural outcome when respondents provide point estimates of statistical distributions on a Likert scale. According to him, central tendency exists even when the survey is well-designed, and thus, it cannot be completely eliminated. However, this should not be an excuse for sub-optimal survey design, which can significantly exacerbate the situation.

There is also a debate in the literature regarding the inclusion of a midpoint on the Likert scale, i.e., designing a survey with an odd number of possible responses. Chyung et al. (2017) argue that the midpoint on the scale can serve as a sort of "dumping ground" for respondents who, for various reasons, do not wish to reveal their true type. They also observe that removing the midpoint leads to a significant increase in non-responses or, in another case, that respondents with a central tendency bias randomly choose one of the two middle responses on a scale with an even number of options.

To avoid central tendency bias, it is also necessary (or at least helpful) to ensure that respondents have an adequate incentive to approach the survey seriously. If respondents have no vested interest in completing the survey responsibly, they may try to expedite this "obligation" (or promise) as quickly as possible. Even in a survey with forced ranking, depending on its technical design, one possible way to do this might be for them to provide the same answer ranking for each task, as this requires no mental engagement and is likely the quickest way to propagate through the survey form.

METHODOLOGY AND RESEARCH HYPOTHESIS

We will address the issue of central tendency by *requiring* survey participants to rank five provided answers according to their preferences rather than simply selecting one. Each ranking of the five elements constitutes a unique response, and since this involves permutations, the number of possible responses is $1\times2\times3\times4\times5 = 5! = 120$. This approach necessitates carefully formulating survey questions to ensure the options are not too disparate, thereby avoiding obvious preference orderings. While this method allows for more nuanced responses, it may not apply to all types of survey questions.

The plan was then to conduct such a survey with an adequately large number of respondents, in this case students, and to apply basic statistical analysis to the types of answers (*not the student attitudes themselves*) to assess whether any overall consistency emerged in the large pool of responses, which could indicate the presence of phenomena similar to central tendency or acquiescence bias. However, since we collected a large number of student responses, we will also briefly discuss the results regarding their attitudes because it is always interesting.

To begin, we will clarify the type of survey in question using an example. Let us assume the respondents are students tasked with ranking five business practices, described in simple sentences, commonly (or even unequivocally) considered unethical. The participants must rank these five sentences according to how they perceive the relative severity of the unethical behaviors described, placing the behavior they view as the most unethical first and the least unethical last. In that way, the degree of severity of unethical behavior is coded with the relative ordering. If the survey instructions specify that each respondent *must* provide an answer and it is not possible to assign the same ranking to more than one option, then the survey essentially employs forced ranking.

HYPOTHESIS

Given that a set of five elements yields 120 possible permutations, our primary research hypothesis formulated prior to designing and implementing the questionnaire was as follows:

H0: A strategy equivalent to resorting to a median answer is not feasible.

This is based on the assumption that such a strategy would be too difficult to execute, as there is no single neutral response available, and the large number of permutations makes it unlikely that respondents could intuitively grasp the full set when completing the survey

quickly. This complexity would make selecting the most neutral option challenging. The alternative hypothesis is therefore:

H1: A strategy equivalent to resorting to a median answer is feasible.

To test this hypothesis, it is essential to employ methods that are as unbiased as possible – that is, methods that remain independent of the survey creators' or respondents' opinions. Our goal is to seek evidence in support of H1, which would mean that H0 is false. If we are unable to provide such evidence, we will retain H0 as valid. This methodological approach is critical, as we aim to use an example (a survey with many respondents, though ultimately a single case study) to explore whether there is any evidence (or at least a strong indication) that could suggest the invalidity of H0.

METRICS USED FOR THE TESTING OF THE HYPOTHESIS

The only way to test the effectiveness of the survey design described above is to collect as many responses as possible and check for any signs of systematic behavior that could indicate avoidance of revealing the true type.

In the survey we will describe later, we asked respondents (students) to answer as many as fifteen tasks. In each task, five descriptions of certain unethical practices in academic and business activities were provided, which needed to be ranked in descending order of unethicality as perceived by each correspondent. The incentive system for responsible participation in the survey was clearly explained in the preamble of the survey. A total of 220 students correctly completed the survey.

Each of the 120 possible permutations for each task was encoded into a single natural number using lexicographic encoding (Wikipedia, 2024b). For example, if integer numbers 1 to 5 enumerated the descriptions of practices offered in each task, the ranking 1, 2, 3, 4, 5 was encoded as the number 1, while the ranking 5, 4, 3, 2, 1 was encoded as the number 120. All other permutations, ordered "as in a dictionary," fall between these extremes.

Converting abstract ideas into numerical values is often difficult and rarely straightforward/linear. For example, imagine three concepts: A, B, and C. Now, to make a statistical analysis easier, assign them numerical values, like n(A), n(B), and n(C). Even if the numerical gaps between them, such as n(A) – n(B) and n(B) – n(C), are equal, this doesn't mean the actual differences between the ideas themselves, A and B or B and C, are equally significant.

Adding more response options to a survey, such as increasing the number of points on a scale, can make it more difficult for respondents to select an answer. In our view, using a Likert scale with more than five options, or even an analog scale, is unlikely to improve the quality of information obtained. This is because each respondent may have a unique system of ideas that cannot be effectively mapped onto a highly detailed, one-dimensional numerical scale in a meaningful way, nor can it necessarily be directly compared to other respondents' systems of ideas. Therefore, it is generally better to keep the categories of ideas broad and, if possible, mutually exclusive, resulting in a smaller number of distinct numerical representations for respondents to choose from. However, we have not conducted research to confirm this hypothesis.

By observing the descriptive statistics of the responses provided by each student across the fifteen tasks, it should be possible to detect any occurrence of rapid completion of the form, indicated by offering the same responses to all (or many) of the fifteen tasks. Such a practice would mimic the central tendency in conventional Likert scale surveys.

BASIC DESCRIPTIVE STATISTICS

The descriptive statistics we used were mean, median, standard deviation, skewness, and kurtosis. For exact mathematical definitions and detailed explanations, see Newbold et al. (2013) or any other good textbook on statistics. For the reader's convenience, we briefly describe those parameters here:

- The *arithmetic mean* represents the "central value" of a dataset, calculated by dividing the sum of all observations by the number of data points. It is a key measure used to summarize the overall "location" of the data.
- The *median* is the value that separates the higher half from the lower half of a dataset. In an ordered list of all elements, it is the value located at the middle position. Unlike the mean, the median is resistant to the influence of outliers, making it a particularly useful measure of the data's central point in skewed or non-Gaussian distributions.
- *Standard deviation* provides a quantitative measure of dispersion, indicating the degree to which data points deviate from the mean.
- *Skewness* quantifies the asymmetry of a probability distribution. Positive skewness denotes a longer right tail, whereas negative skewness indicates a longer left tail. A skewness value near zero indicates an approximately symmetric distribution. In our dataset, skewness does not help analyze the distribution of responses for an individual correspondent because the numerical codes for responses are *de facto* arbitrary and carry no intrinsic meaning. However, it can, at least in some cases, when the data are grouped by task, become an informative parameter that describes aspects of the response distribution for the collective of many correspondents answering the same question.
- *Kurtosis* measures the tails and peak of a distribution relative to a normal distribution. Excess kurtosis, which compares the kurtosis value to that of a normal distribution, identifies whether a distribution exhibits fatter tails (leptokurtic) or thinner tails (platykurtic), providing insight into the likelihood of extreme deviations. High kurtosis may signal the existence of extreme outliers, but more importantly, it can indicate potential bimodality, which would suggest a grouping of responses around two dominant answers instead of one, for example, when respondents are divided in their ethical attitudes. This is also potentially (but not necessarily) useful when the data are grouped by tasks (not by respondents) as it enables spotting the possibly divided responses from a large dataset more easily.

It should be noted, however, that the numerical values of the codes representing the permutations of responses have no relation to the content (or, in this case, the ethical dimension) of the sentences presented to the survey participants for ranking.

CONCENTRATION MEASURES

We used another set of descriptive statistical measures to assess the *concentration* of the responses given to any of the tasks, Q1 to Q15. Given the fact that in any society or group, certain prevailing ethical attitudes exist regarding any question of ethical importance, it is expected that the responses to each Q would cluster around a particular option. High concentration could indicate a strong group preference toward a specific option, whereas low concentration may suggest a weak preference. However, an excessively high concentration, especially if observed across multiple tasks or for particularly "simple" orderings (e.g., 1 2 3 4 5), might indicate similar behavior exhibited by many respondents, with or without coordination. Conversely, a concentration that is too low could raise suspicions about possible random answering. Both circumstances would undermine the basic credibility of the survey results. Ideally, the concentration indices would assume "moderate values," which, by necessity, remains a subject of interpretation. Naturally, those values are expected to be (possibly even significantly) different for different Q's.

We evaluated several concentration measures to determine which would be most appropriate for our purpose:

- *Herfindahl-Hirschman Index* (HHI) (Calkins, 1983),
- *Gini Index* (Gastwirth, 1972),
- *Concentration Ratio,* (CR_m), defined as the sum of the mmm largest shares (see Wikipedia, 2024a),
- *Zipf's Law parameters* (Wikipedia, 2024d),
- *Other non-parametric measures*, such as the rank at which the relative frequency is half that of the top-ranked permutation, the number of permutations receiving at least one vote, and the average share of all voted permutations.

After a thorough comparative analysis, we found that the HHI was the most selective indicator and exhibited the best overall consistency with all other measures. Therefore, we chose to report only the HHI results and the corresponding conclusions in this paper.

The *Herfindahl-Hirschman Index* (HHI) is the sum of the squares of the percent "market shares" of all individual entities active in that "market." In our context, we regard any of the 120 possible answer permutations in each Q as an entity (a "market player") that captured a certain number of respondents' votes. In our case, that number, denoted as x, can take any integer value between 0 and 220. The "market share" of a permutation is calculated as $s = 100\ (x/220)\%$. The HHI equals the sum of the squares of all 120 s-values. Consequently, the HHI can take any value between 0 and 10,000. The larger the HHI, the greater the inequality between individual shares, indicating a higher degree of concentration of votes. If all shares were equal, the HHI would take the smallest possible value of 10,000/220 = 45.45. If all votes went to a single permutation, the HHI would equal 10,000. The effective number of hypothetic entities equals $N_{eff} = 10,000/\text{HHI}$. This is the number of entities giving the same HHI if all had equal shares.

SURVEY DESIGN AND TEST RESULTS

In this section, we describe the design of the survey and the statistical tests performed to detect indirect evidence of systematic behavior by individual respondents, which might indicate central tendency bias or similar patterns.

As previously mentioned, the survey consisted of fifteen tasks. We marked them as Q1 to Q15. Each task included five sentences describing academic or business practices typically considered unethical, and respondents were asked to rank them based on their perceived severity, from the most to the least harmful. All tasks and the corresponding sentences that had to be ordered are listed in the Appendix 1.

Additionally, respondents were asked to rate each task as a whole according to the general severity of the ethical practices described in the following categories:

- A: Light or not very severe;
- B: Medium severity;
- C: Very severe and/or harmful.

As this part of the survey was not used for our study of eliminating the central tendency bias, it was not subjected to statistical testing.

Yet, because of that, the survey designer had to ensure at least relative consistency in the overall degree of severity across each group of five descriptions to avoid combining very different scenarios that would likely lead all respondents to favor (or disfavor) a specific option or range of options. For example, if a task includes four descriptions of relatively mild unethical behaviors, such as "surfing the Internet during lectures," alongside a severe one, such as "submitting a plagiarized master's thesis," the vast majority of respondents would assign the worst ranking to the latter, even if this choice did not fully reflect their true beliefs. This would effectively reduce the number of meaningful response combinations from 120 (5!) to 24 (4!), as the severe option would practically always occupy the same position. In this way, the designer would create an ideal dumping ground for respondents wishing to signal their (true or contrived) ethicality, as the ordering of the remaining four practices would become inconsequential compared to the one that is clearly the worst.

Regarding the technical design of the survey, limitations in the e-learning software available at the time at the University of Zagreb, Faculty of Electrical Engineering and Computing, prevented the creation of a web form that would allow for simple sorting of five elements into permutations, e.g., by "click-and-drag." Consequently, the survey was administered as an MS Word file, and students were required to manually input their preferred order of answers for each task by entering the letters *a* to *e* (*a* marking the most unethical practice) in cells adjacent to each answer. As a result, post-survey validation was necessary to identify students who inadvertently assigned the same ranking more than once in any task. Of the 226 respondents, six made such errors. Their surveys were excluded from further analysis, leaving 220 valid responses. As explained earlier, these responses were coded into numbers from 1 to 120.

Additionally, the e-learning tool did not allow for random shuffling of the five options within each task. Consequently, the survey designers needed to carefully arrange the options to

avoid repeatedly presenting the same type of order. For example, if the least severe unethical practices consistently appeared first in the list of options and the most severe ones appeared last, respondents might be inclined to replicate this ordering across all tasks. This would effectively create a "dumping ground" for the most socially acceptable responses, mimicking the central tendency effect often observed in traditional Likert scales.

Having a "click-and-drag" or similar convenient feature may, in fact, exacerbate issues similar to central tendency bias in Likert scale-based surveys. For instance, if the interface allowed respondents to easily rearrange answers by dragging, they might be tempted to complete the survey swiftly by leaving all the responses in the default order. Combined with shuffling, this setup could lead to a situation even more problematic than central tendency bias: it would introduce bias similar to central tendency but without any consistent patterns to observe due to random ordering. As a result, we might mistakenly conclude that responses are unbiased. This example underscores the *importance of careful survey design* in terms of both content and technical setup.

DESCRIPTIVE STATISTICAL ANALYSIS RESULTS – TESTING THE HYPOTHESIS

To evaluate Hypothesis H0 we conducted several statistical tests to identify any traces of systematic manipulation by the respondents and to detect potential survey design flaws that might encourage or incentivize them to avoid reporting their true preferences. *No evidence was found to suggest systematic tendencies indicating intentional or unintentional misrepresentation of respondents' true preferences caused by any reason. In this subsection, we will present the analysis supporting this conclusion*.

Figure 1 provides, as an example, a list of numerically coded types revealed by twenty randomly selected respondents. The bars in the cells corresponding to the numerical codes offer visual information, making it easier to observe the general characteristics of the answers across both dimensions – the respondents and the tasks.

	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15	#16	#17	#18	#19	#20
Q1	65	96	114	72	66	42	114	120	66	120	119	118	23	65	72	106	119	18	66	2
Q2	102	89	89	84	54	119	119	107	113	118	82	108	65	89	77	119	119	89	108	84
Q3	67	85	37	45	67	69	67	93	95	44	115	67	91	43	91	109	45	67	69	93
Q4	14	20	14	31	64	20	32	7	56	120	79	61	111	96	7	8	13	20	37	79
Q5	91	19	43	91	2	68	62	18	65	1	44	92	87	92	93	13	44	92	42	31
Q6	2	17	6	1	1	4	3	1	3	7	72	31	75	9	17	9	3	5	27	5
Q7	10	8	6	40	12	10	12	40	18	24	2	30	4	6	2	10	18	12	34	12
Q8	26	89	25	103	65	56	57	1	32	117	33	49	93	57	55	57	49	85	120	30
Q9	8	7	20	48	36	9	14	24	7	4	4	17	8	66	42	3	23	96	26	56
Q10	52	58	34	76	85	58	63	61	97	111	4	104	12	100	73	80	109	111	111	111
Q11	63	93	13	69	7	15	19	62	13	85	6	7	73	7	15	13	85	13	15	13
Q12	46	66	24	70	118	22	20	62	79	7	24	4	91	39	94	40	46	19	46	34
Q13	6	7	30	58	30	30	6	6	2	4	120	6	101	6	5	6	60	54	6	30
Q14	34	5	37	8	6	23	36	27	120	31	4	22	1	20	1	16	34	16	7	15
Q15	42	38	83	59	108	108	65	106	116	106	51	93	107	114	78	118	102	104	77	106
Avg.	41.87	46.47	38.33	57.00	48.07	43.53	45.93	49.00	58.80	59.93	50.60	53.93	62.80	53.93	48.13	47.13	57.93	53.40	52.73	46.73
Stdev.	31.50	36.79	32.12	28.82	38.42	35.64	36.60	41.79	43.70	51.35	44.58	40.74	40.99	38.51	36.76	46.30	39.42	39.89	37.64	38.14
Skew.	0.44	0.21	1.35	-0.51	0.33	0.98	0.80	0.45	0.01	0.08	0.42	0.26	-0.54	0.05	-0.12	0.64	0.42	0.14	0.61	0.55
Stdev./Avg.	0.75	0.79	0.84	0.51	0.80	0.82	0.80	0.85	0.74	0.86	0.88	0.76	0.65	0.71	0.76	0.98	0.68	0.75	0.71	0.82
Median	42	38	30	59	54	30	36	40	65	44	44	49	75	57	55	16	46	54	42	31
Kurtosis	-0.76	-1.88	1.03	-0.15	-0.93	0.12	-0.11	-1.25	-1.59	-2.04	-1.31	-1.53	-1.49	-1.51	-1.84	-1.46	-1.19	-1.90	-0.81	-1.27

Figure 1. A list of the types assigned by twenty randomly selected respondents, with descriptive statistics for tasks Q1 to Q15

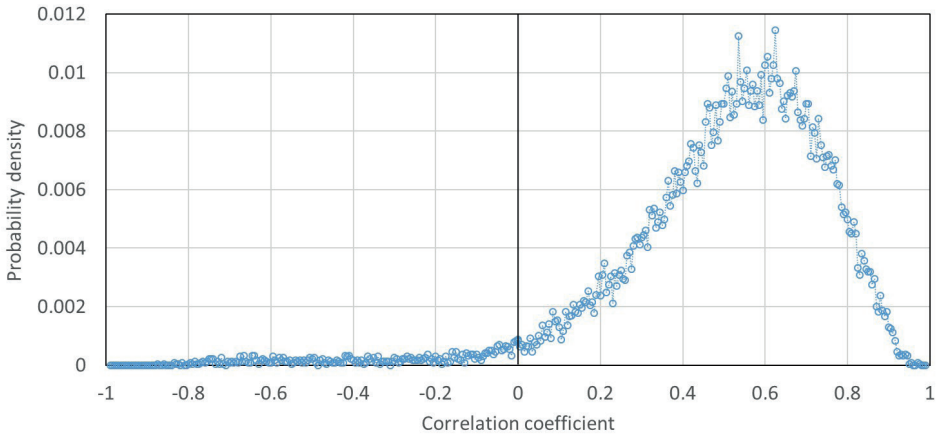

Figure 2. Probability distribution density of the set of all pairwise correlation coefficients between the responses of all 220 respondents for tasks Q1 to Q15. The total number of pairs is 24,090

Regarding the responses to the quandaries posed in each task, one can observe a general similarity in individual student responses, which is expected. It is likely normal for a group of young people attending the same higher education institution and living in the same culture to share at least some general ethical attitudes. However, it is important to note that the responses were not identical, suggesting that the respondents did not collaborate while completing the survey, which is a favorable outcome.

Figure 2 presents the probability density function of the set of all pairs of response vectors provided by the 220 respondents. By "response vector," we refer to a sequence of fifteen numerical codes corresponding to the types assigned by an individual respondent for tasks Q1 to Q15. Therefore, there are 220 response vectors, resulting in 24,090 pairs.

The distribution density shown in the graph is significant. First, the occurrence of negative correlations is very low, indicating that the proportion of students with ethical attitudes diametrically opposed to the majority is minimal, which is expected. The peak of the distribution density is at correlation coefficients around 0.57, corresponding to a low Pearson determination coefficient of 0.32. This suggests a generally vague alignment in the ethical attitudes of the majority of students, with notable differences in individual responses, which is also anticipated. Finally, the proportion of respondents with highly similar attitudes, characterized by a correlation coefficient of 0.9 or higher, is extremely small. These respondents are represented in the far-right portion of the graph. Also, the pairs of students with a correlation coefficient greater than 0.95 are almost non-existent, while the perfect correlation was not observed at all. This means that no one coordinated their work on the survey with anyone else. *Therefore, we conclude that the respondents gave their own types independently*.

The data inspection and the descriptive statistics (see the examples in the lower part of Figure 1) clearly show that none of the respondents applied a strategy of providing the same or very similar responses across all tasks. Therefore, *we can conclude that there was likely*

no "cheating" with the intent of completing the survey as quickly as possible. There was no evidence of a "dumping ground." On the contrary, nearly all students provided very diverse responses to tasks Q1 to Q15. This also suggests that the design of the survey did not encourage any form of "wrongdoing," despite the absence of random shuffling of the five options presented in each task.

Table 1 provides insight into the basic statistical properties of the responses to individual tasks across all respondents. It is noteworthy that the average and median responses vary, indicating that the survey design successfully avoided a systematic pattern of similar ordering by the severity of ethical situations. The standard deviations also show significant variation, suggesting that some tasks elicited more consistent responses while others did not. High kurtosis values may indicate potential bimodality, possibly reflecting divided attitudes among respondents. Using the actual survey results, we will later explore whether these statistics are of any practical use.

Table 1. Descriptive statistics of the responses to individual tasks Q1 to Q15 provided by all 220 students

No.	Avg.	Stdev.	Skew.	Stdev./Avg.	Median	Kurtosis
Q1	87.0	28.27	–0.45	0.32	89	–0.71
Q2	102.11	17.71	–1.72	0.17	108	4.12
Q3	71.28	24.64	–0.22	0.35	73	–0.60
Q4	33.27	30.85	1.22	0.93	20	–0.56
Q5	56.56	28.59	0.08	0.51	48	–0.96
Q6	18.72	27.84	2.16	1.49	5	4.00
Q7	18.58	17.70	2.13	0.15	12	6.62
Q8	59.94	35.04	0.18	0.58	56	–1.06
Q9	43.19	32.53	0.62	0.75	37.5	–0.68
Q10	72.55	38.67	–0.51	0.53	85	–1.17
Q11	21.24	22.12	2.32	1.04	13	5.03
Q12	42.10	26.65	0.82	0.63	40	0.07
Q13	25.30	24.95	1.53	0.99	28	2.13
Q14	24.30	23.29	1.61	0.96	16	3.20
Q15	82.64	29.00	–0.79	0.35	90	–0.08
Aver.	50.59	27.19	0.60	0.70	47.5	1.36

As the final part of our search for evidence of systematic issues typically associated with classical Likert scales, we will examine the *concentration measures* of the response sets for tasks Q1 to Q15. In this analysis, we will treat each of the possible five-element permutations as a member of the set that received a certain number of "votes." The total number of votes across all 120 options is always 220, corresponding to the total number of respondents. The concentration measures used in the analysis are described in Section 3.2.2.

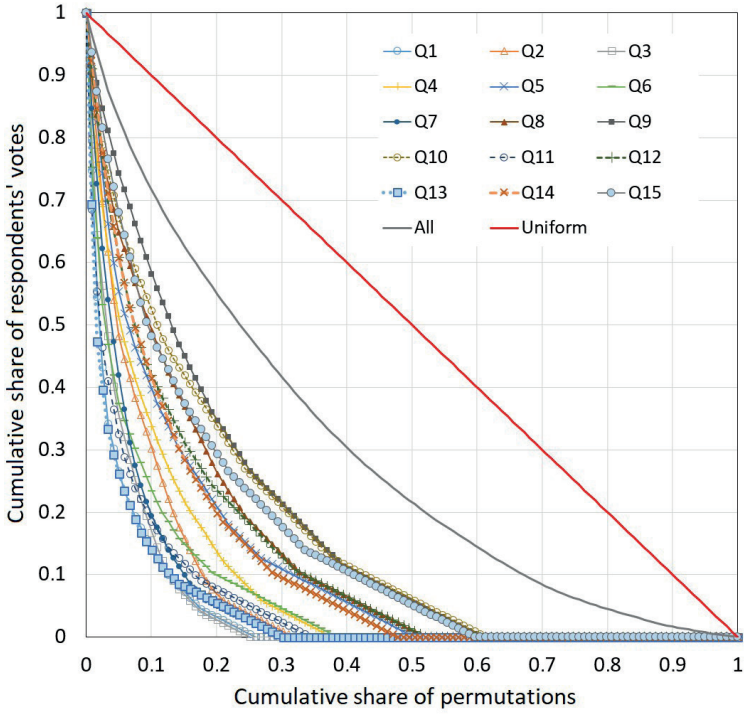

Figure 3. Complementary Lorenz functions for the answer permutation frequencies observed in each individual task and all the tasks, compared to the hypothetical uniform frequency distribution

Table 2. HHI indices for the concentrations of answer permutations in the individual tasks and all tasks, sorted by descending HHI

No.	Q13	Q11	Q1	Q6	Q3	Q7	Q2	Q4	Q5	Q14	Q12	Q8	Q10	Q15	Q9	All
HHI	1586	1361	1325	996	946	746	573	572	434	382	381	339	299	294	239	136

Table 2 presents the HHI figures for each task individually, as well as for all tasks combined, sorted in descending order of HHI. Note that calculating a concentration measure for answer permutations across all fifteen tasks does not hold any content-specific meaning. However, it can be instructive to observe if there is any general tendency to offer formally the same permutations of answers on entirely different tasks, which could indicate some form of "wrongdoing." As shown, the HHI for all tasks combined is very low, suggesting that *no such tendency was present*.

For the individual tasks, a range of HHI values can be observed, with no obvious clustering. The index varies from 239 (for Q9) to 1586 (for Q13), indicating low to moderate concentration levels. A high concentration, defined as an HHI exceeding 2,000, was not

observed. Combined with the results shown in Figure 2, this supports the conclusion that *no "dumping ground" behavior was present in the survey*.

For a visual illustration of concentration, we will use the complementary Lorenz curve (Figure 3), presenting the share of answer permutations (abscissa) awarded cumulative vote shares greater than or equal to the corresponding ordinate value. (It is self-understood that the cumulative share of votes cannot be greater than one.) While the HHI summarizes the information on concentration into a single number that is easy to compare across different datasets – in this case, the tasks Q1 to Q15, the complementary Lorenz curve provides a complete picture of inequality across the entire distribution.

Note that the alignment of the curves generally corresponds to the order of the HHI indices, though not always. For example, while the Q13 curve is mostly the leftmost for higher vote shares, this is not the case for the lower ones. The Q9 curve is the rightmost (widest) overall, but this alignment does not hold at lower vote shares. The Q15 curve remains mainly to the left of Q10, even though it has a slightly lower HHI. Aside from these technical details, it is worth noting that even the least concentrated tasks deviate significantly from a hypothetical uniform distribution, *indicating that random responses were extremely unlikely*. Conversely, while some distributions show somewhat higher concentration around a particular answer, all exhibit sufficient diversity to rule out "dumping ground" behavior. This is further evidenced by the examples in Figure 1.

Based on the statistical tests conducted on the case study with a sample of 220 respondents, as presented in this article, *we found no evidence or indication of behavior equivalent to systematically resorting to a neutral (or any other particular non-true type) option*, which would resemble central tendency bias in traditional Likert scale-based surveys.

Therefore, we can retain the null-hypothesis H0 from Section 3.1.

REFLECTIONS ON THE STUDENT ATTITUDES OBTAINED FROM THE SURVEY

The respondent group comprised 220 students who completed the entire survey without errors. These students were second-year undergraduates enrolled in the course "Engineering Economics 1" at the Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia (https://www.fer.unizg.hr/en/course/engeco1). This course, covering introductory microeconomics, is designed to provide students majoring in electrical engineering and/or computing with an introduction to economics and business. A related voluntary activity, the "Business Workshop", invites external professionals to give talks and practical sessions on various aspects of working in the business sector. The respondent group included 48 female students, representing 21.8% of the total – a percentage closely aligned with the overall proportion of female students at the Faculty (Samuelson et al., 2022). The survey was conducted in June 2022.

In this research, we did not conduct any analyses that considered potential statistical differences between the responses of male and female participants. Given our primary research objective, we deemed this unnecessary. Moreover, in the results stated above, we found no

evidence of any "manipulative" behavior, so dividing the population into these two groups would hardly yield conclusions different from those presented earlier. For example, previous research comparing student attitudes toward entrepreneurship education in Croatia and Slovenia found no significant gender-based differences (Potocan et al., 2016).

However, given the extensively documented gender gap in STEM fields (OECD, 2008; Ceci et al., 2009), it may be interesting to investigate whether there are statistically significant differences in survey response behavior dependent on the gender of the STEM students, but we will leave it for future research.

THE IMPORTANCE OF BUSINESS-RELATED CONTENT FOR STUDENTS IN STEM FIELDS

Higher education institutions are pivotal in nurturing students' intellectual development and laying the foundations necessary for economic progress in societies that rely heavily on knowledge and innovation (Drucker, 1969; Powell and Snellman, 2004). To optimize the benefits of university education, faculty and academic programs strive to offer courses that resonate with students' interests and attitudes, recognizing these as powerful motivators that drive engagement and academic success (Krapp and Prenzel, 2011). For STEM students in particular, fostering an interest in business not only sharpens their technical skills but also expands their grasp of the economic and business contexts in which these skills will be applied.

Research has demonstrated that students are more likely to excel in subjects they perceive as relevant and engaging. Studies on technological literacy, for example, show that interest correlates with higher achievement and deeper mastery in a field (Svenningsson et al., 2018). Accordingly, identifying and supporting student preferences helps faculty and academic programs tailor courses that both appeal to students and contribute to their academic advancement.

Mazzola et al. (2023) show that students who completed a graduate-level ethics course developed a stronger ethical awareness and a greater tendency to consider the societal impact of their work compared to peers who hadn't taken the course. They examine how ethics courses resonate with students, especially when discussing real-world cases that connect their technical work with broader ethical implications. These insights suggest that engineering students find value in such content as it directly influences their professional and personal perspectives on ethics.

We believe it is unsurprising that young people show a strong interest in ethics and highly value its principles. This interest drives their enthusiastic engagement with courses focused on ethical issues, particularly those related to their prospective careers, enabling educators to expand on foundational ethical concepts in a more systematic and structured way.

REVIEW OF SURVEY RESULTS

As mentioned earlier, our study examines the comparative attitudes toward certain (undoubtedly) unethical practices in business and academia (refer to the Appendix 1), as expressed by electrical engineering and computing students at the University of Zagreb. These students were enrolled in the economics/business-oriented elective course, "Engineering Economics 1".

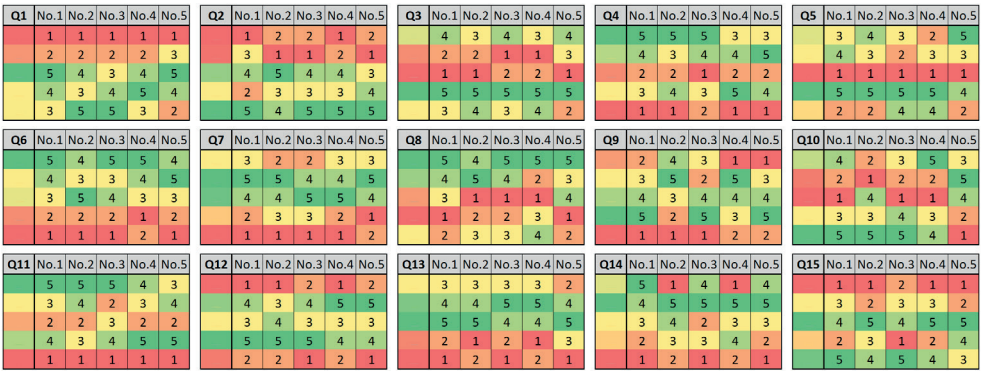

Figure 4. The survey results of second-year undergraduate students in engineering and computing programs at the University of Zagreb. Number of participants: 220. Date: June 2022

Figure 4 provides a comprehensive overview of the survey results. Each block corresponds to one of the tasks, Q1–Q15. The five types with the highest counts are shown in the columns labeled No.1–No.5. The integer values represent answer codes, as listed in Appendix 1. Color codes are applied for easier readability (1 red, 2 orange, 3 yellow, 4 light green, 5 green). The first column in each block is color-coded to represent a weighted average of all code numbers in the respective row, visually indicating the "average answer" for that position among the five most preferred types. The horizontal position corresponds to the relative severity of unethical practice: the first-row position indicates the most severe practice, whereas the last marks the least severe. The results displayed in the table should be "decoded" using Appendix 1. It may be helpful to compare the data in Figure 4 with those presented in Tables 1 and 2.

The color codes are particularly useful for identifying situations where students displayed divided opinions. Specifically, in tasks where the color arrangement remains fairly consistent across all five top-scored types, No.1–No.5, students exhibited similar comparative attitudes with only minor differences. Notable examples include Q1, Q11, and Q13. Conversely, blocks displaying similar colors at both the top and bottom indicate a division in attitudes; examples of this pattern can be seen in Q3, Q5, and Q12. Additionally, left-to-right color inconsistency across the five most frequent types may suggest students' uncertainty or confusion regarding the options they were asked to choose from.

It is essential to interpret these survey results with the understanding that the values in Figure 4, and therefore the colors as well, *carry no intrinsic meaning regarding ethical stances*. They serve merely as codes that facilitate the reading of results in this relatively complex scheme, which is less straightforward than a typical Likert scale-based questionnaire.

After reviewing the graphical presentation of results in Figure 4, along with the qualitative findings partially described in this section, and comparing these with Tables 1 and 2, we found that descriptive statistical measures, such as kurtosis, skewness, and the standard deviation-to-mean ratio, did not show an evident relationship with the most notable examples of highly consistent (e.g., Q1, Q11, Q13) or highly varied (e.g., Q3, Q5, Q12) responses.

Thus, we can preliminarily conclude that these measures may have limited utility on their own. However, this warrants more detailed investigation.

On the other hand, the HHI showed consistency across these examples: tasks with highly consistent responses had higher HHI values (1,325, 1,361, and 1,586, respectively), while tasks with highly varied responses had lower HHIs (946, 434, and 381, respectively). Given the previously noted advantages of HHI in terms of selectivity in concentration measurement, we conclude that the HHI remains the most effective descriptive statistical measure for use in this type of survey.

CONCLUSIONS AND FUTURE RESEARCH

This study introduces a forced-ranking survey design as a methodological approach to mitigate central tendency and acquiescence biases, which are commonly observed in traditional Likert-scale surveys. The method was tested through statistical analysis of survey responses collected in a case study involving 220 engineering students. The primary goal was to detect any systematic avoidance of revealing true preferences. The results showed that the proposed approach effectively eliminated the likelihood of response distortions often encountered in Likert-scale surveys.

The findings also indicate that the Herfindahl-Hirschman Index (HHI) was the most effective metric for analyzing concentration patterns in survey responses, providing consistent results across tasks. While other descriptive statistics, such as skewness and kurtosis, offered some insights, their utility appeared limited in comparison to HHI.

The contributions of this study are both methodological and applicative. Methodologically, it provides a viable alternative to traditional survey designs, offering a means to collect more reliable data while reducing biases. In terms of applicability, the case study illustrates how the proposed method can be used to evaluate response patterns and detect potential manipulative behaviors in survey data.

Future research should focus on further testing the generalizability of this survey design across different populations and cultural contexts. Additional studies could explore whether the methodology is effective in addressing other response biases, such as social desirability bias, and examine the potential integration of automated tools, including AI, to enhance data analysis and interpretation.

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APPENDIX 1

Fifteen tasks (Q1 Q15) in the survey designed to test the Hypothesis, with five sentences (answers) per task to be ordered by ascending perceived ethical severity:

Q1

1. Secretly copying or completely replicating someone else's seminar paper.
2. Paying an acquaintance or friend to write a bachelor's thesis.
3. Ordering a thesis on a given topic from an unknown person on the Internet for a fee.
4. Copying from "cheat sheets," the web, etc., and/or seeking help from other classmates during an exam.
5. Assisting other classmates during an exam.

Q2

1. Plagiarizing someone else's scientific paper (in significant parts or entirely) without citing the source.
2. Incorrectly and/or incompletely citing works used in research, or not mentioning those works at all.
3. Slightly modifying research results to more easily justify the study's conclusions.
4. Adding a colleague to the list of co-authors, even though the person did not significantly or at all contribute to the work.
5. Using Internet sources while writing a scientific paper without citing those sources.

Q3

1. Neglecting developments in the field being taught and delivering the exact same lectures for years.
2. Accepting a modest amount of money or other small benefits for a better grade or a passing mark.
3. Finding pirated textbooks on the Internet and providing links to students "so they can find them themselves."
4. Overlooking students' mistakes during grading.
5. Presenting unverified information during lectures based on the logic that "No one will notice anyway."

Q4

1. Surfing the Internet during lectures (as a student) or work hours (as an employee), unrelated to the lecture topic or job.
2. Using software obtained from a friend who did not acquire it legally.

3. Lending or giving software legally acquired to a friend or colleague.
4. Using software found on the web that does not have a legal license but was uploaded by someone else, thus blaming that person.
5. Selling a copy of legally obtained software to a colleague or friend.

Q5

1. Downloading pirated software from the Internet.
2. Distributing pirated software from the Internet to others.
3. Purchasing one legal software license and then installing it on multiple computers.
4. Helping others access pirated software from the Internet and install it on their devices.
5. Freely using everything found on the Internet without considering its origin, as long as someone else put it there (because that other person is responsible).

Q6

1. Poor (careless, negligent) protection of confidential information they work with (e.g., not using passwords, using weak passwords, leaving documents visible on the desk or screen…).
2. Not reporting a colleague who provides confidential information to unauthorized persons.
3. Providing unauthorized persons access to confidential personal information.
4. Giving confidential commercial information to unauthorized persons without requesting compensation or a favor in return.
5. Requesting compensation or a favor in return for providing confidential commercial information to unauthorized persons.

Q7

1. Bypassing a minor rule if it will speed up/improve the completion of a work task.
2. Exploiting information one has access to in their job, which others do not, for personal interest or advancement at work.
3. Indiscreetly sharing someone else's sensitive personal information learned while performing their job.
4. Deliberately misinterpreting regulations/codes to uninformed or younger colleagues to potentially share future blame for non-compliance.
5. Not reporting observed non-compliance with regulations/codes by other colleagues.

Q8

1. Participating in phishing (unauthorized fraudulent collection of other people's valuable data).
2. Participating in spoofing (forging emails for phishing purposes).

3. Engaging in unauthorized monitoring of people's activities through tracking devices/applications.
4. Using the Internet and new technologies to harm others (e.g., cyberbullying, creating fake profiles on social networks to damage reputations, deep-faking, etc.).
5. Publishing someone else's personal or valuable data on the Internet or social networks.

Q9

1. Creating large mailing lists and spamming recipients with messages of unknown interest.
2. Selling (or even giving away) one's mailing lists to others without the consent of the individuals on the lists.
3. Buying mailing lists from others who created them while doing their legitimate business.
4. Not providing users on the mailing list with a simple option to unsubscribe.
5. Not caring about potentially unacceptable/offensive content for some users on large, otherwise legally and correctly acquired mailing lists.

Q10

1. Teasing colleagues based on their physical appearance, dress style, etc.
2. Constantly criticizing many or even all colleagues at the workplace.
3. Being careless regarding the quality and scope of work performed.
4. Avoiding part of one's job duties so others have to do them.
5. Constantly criticizing only one particular person or a few individuals at the workplace.

Q11

1. Hiring a relative who is proven to be competent for the job.
2. Hiring a person who is otherwise proven or likely to be incompetent upon someone else's request, to do a favor.
3. Hiring a proven competent person for a job that is unnecessary.
4. Hiring a proven incompetent person for a necessary position.
5. Not hiring a competent person due to their racial background.

Q12

1. Exercising discretionary authority to appoint a proven highly competent person, even though another person received higher scores based on public competition criteria.
2. Appointing a person of unknown managerial qualities based on the request of another person, as a favor.
3. Appointing a person who is highly loyal and inclined to flattery but lacks significant managerial qualities.

4. Appointing a person who shows dictatorial management characteristics.
5. Appointing based on a formal public competition, where the criteria are set to significantly increase the likelihood that a specific, otherwise very competent person will receive the highest score.

Q13

1. Approving travel expenses for an official trip that was not made to provide some financial assistance to the employee.
2. Allowing the use of a company vehicle for personal purposes for an employee who does not have that right in their contract with the employer.
3. Withholding overtime pay, even though such work is often required of employees.
4. Intentionally setting unrealistically high goals for employees so that they can constantly be blamed for failure.
5. Tolerating and protecting employees who do not try hard enough and have poor work results.

Q14

1. Setting the conditions for a public tender for the procurement of strategic semi-finished products and raw materials so that a specific very reliable and quality supplier wins, even if it is slightly more expensive than others.
2. Adjusting accounting policies so that indicators visible from financial statements signal a better state than the actual one, which positively affects the stock price, thus benefiting shareholders.
3. Deciding to invest in a very risky, high-value project without detailed prior analysis of the project itself or analyses of ways to mitigate the risks associated with it.
4. Setting conditions for a public tender for the procurement of strategic semi-finished products and raw materials so that a specific supplier wins in exchange for a certain amount of money as a bribe.
5. Downplaying the environmental risks associated with constructing a new production facility to more easily obtain consent from the local community on whose territory the facility will be built.

Q15

1. Unfair treatment of business associates and other people of different nationalities, religions, genders, sexes, sexual orientations, etc.
2. Manipulating information/lying to mislead uninformed people and thereby achieve some benefit for the company in which one works or manages.
3. Careless handling of hazardous waste generated in production to reduce costs associated with the company's obligation to dispose of such waste.

4. Ignoring the adverse psychological effects that poor interpersonal relationships within the company may have on some or all of its employees.
5. Prioritizing the business interests of the company in which a person works while simultaneously disregarding the interests of society, the state, or the local community related to the company's activities.