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Analysis of the Application of Quality Criteria in Public Procurement of Construction Sector

Master's thesis

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Abstract

Public procurement of construction sector accounts for about 50 % of the value of all public procurement (excluding low-value procurement). The projects of this sector are usually long-term, therefore it is important to find tools that would help to perform works with quality. Application of quality criteria - a tool for contracting authorities to obtain the most economically beneficial offer. Since the application of quality criteria has not only advantages, but also emerging risks and disadvantages, in order to find out what can influence the decision made by the contracting authorities to use quality criteria in the public procurement of the construction sector, a survey was conducted. Structural equation modeling analysis was performed on the obtained data. Results show, that doubts that procedures where quality criteria are applied will be successful, leads to the fact that these criteria should not be used. The application of the mentioned criteria is also reduced by insufficient knowledge of the public procurement system (laws, legal acts related to construction) and greater competition in the mentioned sector, which can be decisive for greater participation in procurement, but also complicates the evaluation process. In addition, the results show that the greater experience in application of quality criteria and lack of knowledge of the procurement system, leads to the fact that the contracting authorities believes that the application of such criteria is difficult. The more complex the appearance, the more it is accepted that the procedures will end unsuccessfully by applying quality criteria.

Keywords: public procurement, construction sector, quality criteria, Exploratory Factor Analysis, Structural Equation Modelling.

Santrauka

Statybos sektoriaus viešieji pirkimai sudaro apie 50 % visų viešųjų pirkimų vertės (be mažos vertės pirkimų). Šio sektoriaus projektai dažniausiai yra ilgalaikiai, todėl svarbu rasti priemones, kurios padėtų darbus atlikti kokybiškai. Kokybės kriterijų taikymas – įrankis perkančiosioms organizacijoms gauti ekonomiškai naudingiausią pasiūlymą atsižvelgiant ne tik į pasiūlymo kainą. Kadangi kokybės kriterijų taikymas turi ne tik privalumų, bet ir kylančių rizikų bei trūkumų, siekiant išsiaiškinti, kas gali turėti įtakos perkančiosios organizacijos priimamam sprendimui naudoti kokybės kriterijus statybos sektoriaus viešuosiuose pirkimuose, buvo atlikta jų apklausa. Gautiems duomenims buvo atlikta struktūrinių lygčių modeliavimo analizė. Rezultatai rodo, kad dvejonės, kad kokybės kriterijų taikymo atveju procedūros baigsis sėkmingai, lemia tai, kad šie kriterijai mažiau naudojami. Minėtų kriterijų taikymą mažina ir nepakankamas viešųjų pirkimų sistemos išmanymas (įstatymai, su statyba susiję teisės aktai) ir didėjanti konkurencija minėtame sektoriuje, kuri galimai lemia didesnį dalyvavimą pirkimuose, tačiau taip pat apsunkina vertinimo procesą. Be to, rezultatai rodo, kad didesnė patirtis taikant kokybės kriterijus bei pirkimų sistemos nepakankamas išmanymas, lemia tai, kad perkančioji organizacija, mano, jog tokių kriterijų taikymas yra sudėtingas. Kuo sudėtingesnis atrodo taikymas, tuo labiau sutinkama, kad procedūros taikant kokybės kriterijus baigsis nesėkmingai.

Raktažodžiai: viešieji pirkimai, statybos sektorius, kokybės kriterijai, tiriamoji faktorių analizė, struktūrinių lygčių modeliavimas.

Contents

1 Introduction

Public procurement is the main form of state expenditure. In this way, public and budgetary institutions provide themselves with the necessary services, goods and works. In Lithuania the amount of funds spend purchasing construction works, over the period of 2019-2021, on average amounted 3.5 billion euros per year and about 70 % of this amount was purchased through public procurement. Lithuania's construction sector procurement accounts about 50 % in value of all above and below threshold[1] procurement (excluding low value procurement) every year. It amounts about 4,7 % of Lithuania's Gross Domestic Product (GDP). Purchases of the aforementioned sector includes new construction, demolishing old buildings, infrastructure of roads, electricity, gas and repair, installation works. Quality of these works is crucial to spending public funds efficiently.

Most of the projects in construction sector are long-term, therefore quality of it is essential. Pivotal part of selecting the winning offer is picking evaluation criteria. Possible criteria in Lithuania's public procurement system are the following: lowest price, price and quality ratio, cost and quality ratio, cost criteria. Last three are collectively called quality criteria, because during the evaluation process, application of such criteria considers not only the price of the offer. With that in mind, application of other than lowest price criterion is a tool to pursue more efficiency, greater economic benefits. By using them, contracting authorities expect contractors to propose additional conditions, that contracting authority named as conditions that they are, in most cases, willing to pay more, compared to offers that do not propose such conditions. Usage of quality criteria potentially brings contractors who has more experience, suggests innovative solutions, durable materials, etc. For those requirements with a long operating life, it allows the contracting authority to take into account the life-cycle costs of the requirement purchased and not only the direct cost of the purchase or the initial purchase price within the set specifications.

In theory, application of quality criteria can also increase competition, participation of small and medium-sized enterprises. On the other hand, wrongfully used quality criteria can be used to limit competition, thus specific contractor might win procurement procedures. Another obstacle might be the complexity of applying other than lowest price criterion or concern that procedures not only going to take longer time, but also that they would end unsuccessfully, and the process will have to be restarted. When using only price as the criterion, winning bid is the one with the lowest price (as long as the prerequisites are met). In case of applying quality criteria, not only price should be considered. Then the question rise up, how to measure impact of each chosen criteria and what part in the final decision it will take. For that, simulations in order to evaluate the suitability of the chosen formula, the "price" of each criterion and the influence of the comparative weights given to them on the selection of the most economically beneficial offer, could be carried out. The process becomes much more complicated and in most cases the final contract price increases.

Main objective of this paper - determine what influences contracting authorities decision to apply quality criteria in their public procurement of construction sector. To achieve this goal, main tasks

[1] Minimum monetary value of tenders which are presumed to be of cross-border interest if it exceeds it. The European rules ensure that the award of contracts of higher value for the provision of public goods and services must be fair, equitable, transparent and non-discriminatory. For tenders of lower value however, national rules apply, which nevertheless have to respect general principles of EU law.

were formulated:

- literature review of quality criteria application in construction sector and in general;
- conducting survey of Lithuania's contracting authorities about quality criteria application in public procurement of construction sector;
- exploratory factor analysis of conducted survey data;
- structural equation modeling analysis;
- interpretation of final results and determination of influences to the choice of contracting authorities to apply quality criteria in their construction sector procurement.

R program was used for data analysis. Conclusions are presented at the end of the work.

2 Literature review

As construction sector procurement are mostly long term projects, it is very important to find the most economically beneficial offer. For that it is crucial to evaluate the needs of the contracting authority and include them into technical specification and other purchase documents. Clearly prepared tender documentation ensures that broad participation of potential competitors (including small and medium enterprises) can compete with their offer. Providing clear specifications, payment terms, information about evaluation and award criteria (weights of individual criteria) can ensure a smoother process and greater economic benefits [1]. Although public procurement decisions might require the simultaneous use of set criteria, construction sector procurement can be very different depending on what infrastructure is built, repaired or demolished. For that reason mandatory requirements and additional available quality criteria can vary greatly. Some contracting authorities would require few additional criteria when evaluating contractors bid, else can set requirement list with many if they are needed. Too many requirement could lead to less bids, because contractors may not fulfill the needs of procurer, but also would consider that the execution of the contract may be too complicated and would not compete in the procurement procedures [6]. By using quality criteria, contracting authority might ask contractor to offer additional guaranty time, use environmentally friendly materials and systems (BREAM, EMAS), social criteria and etc.

The usage of quality criteria in theory could lead to more competition. More specifically it could promote small and medium-sized (hereinafter - SME) businesses. Usually these enterprises are new and they cannot compete with larger companies that could offer lower price and their experience. Although quality criteria supposed to increase competition, that does not always reflect in practice. In the example of Sweden, no significant effect on SME participation in procurement bids as a result of the use of quality criteria in firm evaluation, were found [2]. According to Adham and Siwar (2017) [4], who investigated factors influencing government green procurement practices using structural equation modelling, supplier availability had significant and positive influence on these practices. This would mean that supplier, contractor availability could also influence the application of quality criteria. On the other hand, with greater competition, comes more offers, that contracting authorities has to evaluate. This might be a reason for authorities not to apply quality criteria to avoid complex procedures. Based on the reports of procurement procedures of construction sector published in Central Public Procurement Information System of Lithuania, average number of offers using quality criteria versus lowest price criterion is the same over the last three years.

Usage of criteria other that lowest price, adds additional administrative costs because of the needs not only to choose needed new criterion, but also deciding on their weight or what kind and what amount of benefit it brings. This requires simulations and decision of what kind of method of evaluation will be used. This process is crucial for several reasons: formula used not only determines the wining offer, but by doing this, it affects the outcome of the project, formula should protect from bids with extremely high prices, representation of weights of price and quality [3]. The process of it, demands not only time, but also knowledge. Preparation process - selecting criteria, conducting simulations - also requires additional time, which would not be needed if bids were evaluated using lowest price criteria [5]. In already mentioned paper of Adham and Siwar [4], uncertainty about the results and lack of practice has influence on implementing instruments under investigation, meaning that the less concerned authorities are about implementation and results of it (specifically unsuccessful procedures), more willingly they might use those instruments. In case of quality criteria, uncertainty about execution of the contract, selection of suitable criteria also could be factors influencing the decision to apply aforementioned criteria.

Knowledge of not only implementation of chosen tools, but also the legislation is important. According to Adham and Siwar [4], knowledge has significant and positive effect on implementing tools for green procurement. Lack of knowledge of public procurement system might have affect on applying quality criteria. Since construction sector is quite specific, there are also many law articles defining procurement in this sector. According to Grandia [8], knowledge of the field has an effect on the application of application of sustainable procurement, meaning that more knowledge authorities has, more they show sustainable behaviour. The same logic could be applied to application of quality criteria. More contracting authorities (their specialists) have knowledge of laws, articles considering their procurement (specifically construction sector), more willingly they might use quality criteria in their procurement.

As there are advantages and disadvantages, that are discussed in literature, of using quality criteria instead of lowest price criteria, which is considered easier, faster, cheaper, many of them comes to a fact that although usage of it is encouraged, only critically selected criterion should be used. Contracting authority must specify what constitutes additional value for the procurement or what it will lead to the selection of one bid over another [6].

3 Methodology

3.1 Data collection

The population – contracting authorities in Lithuania that made conducted public procurement procedures (contract has been concluded) in construction sector in years 2019-2021. Survey was conducted using an online questionnaire. Contracting authorities to whom survey form has been provided, has been selected by using data published by the Public Procurement Office of above and below threshold (excluding low value procurement) procurement. Population size - 729. Survey has been performed in the months of June-July of 2022.

Questions were formulated to fit *the* Likert scale of five points ranging from 1 (strongly disagree) to 5 (strongly agree) was used. Questions were formed based on literature and consultations with specialists of Public Procurement Office. All questions were grouped into 5 groups: usage of quality criteria (UQC), knowledge (K), competition (C), end of procedures (EP), complexity of quality criteria (CQC) (see table 1).

Table 1:

Scale item	Question
UQC1	In the last three years, how often have you evaluated the bids according to quality criteria in construction sector purchases?
UQC2	How often do you carry out simulations when determining the points assigned to quality criteria in order to evaluate the suitability of the chosen formula, the "price" of each criterion and the influence of the comparative weights given to them on the selection of the most economically beneficial offer?
UQC3	In the past year, were environmental protection criteria applied in the construction sector procurement when evaluating proposals using quality criteria?
UQC4	Please indicate the number of employees performing procurement functions only
K1	the organization's specialists lack qualifications in the field of public procurement
K2	the organization's specialists lack qualifications in the field of legal acts regulating construction and technical aspects related to construction
C1	Do you agree with the statement that there are enough suppliers involved in public procurement of new construction works?
C2	Do you agree with the statement that construction reconstruction, repair, etc. are enough suppliers participating in the public procurement of works?
C3	Do you agree with the statement that the procurement competitiveness of the construction sector has been increasing over the past three years?

Continued on next page

Table 1: (Continued)

C4	Does the application of quality criteria increase the competitiveness of procurement in the construction sector?
EP1	Are procurement procedures terminated more often when applying the quality criteria than when applying the lowest price criterion?
EP2	When applying quality criteria, do procurement procedures more often end without receiving a single offer (or application) than when applying lowest price criteria?
EP3	Does the application of quality criteria increase the number of procurement procedures in which all proposals (applications) are rejected as unacceptable, compared to procurement in which the lowest price criterion was applied?
EP4	Do you think that setting and applying quality criteria in your organization's construction sector purchases will result in higher bid prices?
CQC1	Do you think that defining and applying quality criteria in your organization's construction sector purchases will make contract execution more difficult?
CQC2	Do you think that it is difficult to ensure proper supervision of contract execution when determining and applying quality criteria in the procurement of the construction sector carried out by your organization?
CQC3	Do you think that it is difficult to assess the economic benefits of quality criteria?
CQC4	Do you think it is difficult to assess which quality criteria may be the most important depending on the construction site?

3.2 Data analysis

With reference to Khairul Naim Adhams work "Factors Influencing Government Green Procurement Practices: Structural Equation Modeling Analysis" [4], structural equation modeling (hereinafter - SEM) approach was chosen for further analysis. SEM is a set of statistical techniques, models such as analysis of variance, covariance, multiple regression, factor analysis, that is used to measure and analyze the relationships of observed and latent variables. SEM may most often be used as an approach to data analysis that combines simultaneous regression equations and factor analysis. Factor analysis models test hypothesis about how well a set of observed variables in an existing data set measure latent constructs. Latent constructs represent theoretical, abstract concepts or phenomena such as attitudes, behavior patterns, cognitions, social experiences, and emotions that cannot be observed or measured directly or with single items. Factor models are also called measurement models because they focus on how one or more latent constructs are measured, or represented, by a set of observed variables.

4 Findings

4.1 Exploratory Data Analysis

A total of 490 respondents took part in the survey (response rate of 67,2). The final dataset contained 17 columns (columns with unnecessary information – during the survey, the contracting authorities were also interviewed on other issues related to public procurement of construction sector, not related to quality criteria issues). There were no missing values, because all questions included in the analysis were mandatory. Histogram of all variables were plotted (see figures 5–9). Correlation matrix showed that some variables have significant correlations (see figure 1), specially within specified question groups. For example, K1 and K2 has correlation coefficient of 0.62 (moderate positive correlation), meaning that increase in K1 (respondents lack of knowledge / qualifications in the field of public procurement), increases K2 (respondents lack of knowledge / qualifications in the field of legal acts of construction sector).

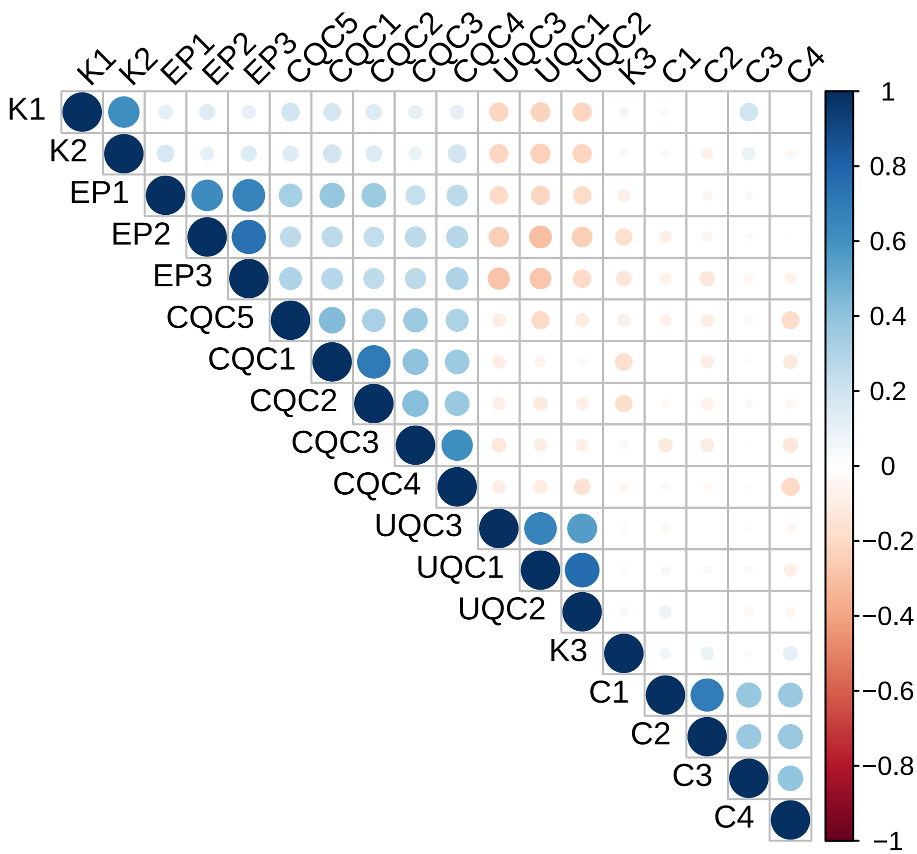

Figure 1: Correlations of variables.

The assumption of multivariate normality was accessed. Shapiro-Wilk's for univariate and Mardia's Multivariate Skewness and Kurtosis tests for multivariate normality were used. Results from both the univariate (see table 2) and multivariate (see table 3) tests indicate that the measures do not come from normally distributed univariate or multivariate distributions - p-values < 0.05 (the 'No' results in the 2–3 tables).

	W	p-value	UV.Normality
K1	0.9164	0	No
K2	0.9031	0	No
CQC5	0.8648	0	No
CQC1	0.8993	0	No
CQC2	0.8984	0	No
CQC3	0.8717	0	No
CQC4	0.8599	0	No
UQC1	0.6631	0	No
UQC2	0.6166	0	No
UQC3	0.5211	0	No
EP1	0.8442	0	No
EP2	0.8301	0	No
EP3	0.8281	0	No
C1	0.8683	0	No
C2	0.8792	0	No
C3	0.8494	0	No
C4	0.8549	0	No

Table 2: Shapiro-Wilk Univariate normality test.

Test	Statistic	p-value	Result
Skewness	4166.6882	0	NO
Kurtosis	25.5819	0	NO
MV Normality	<NA>	<NA>	NO

Table 3: Mardia Multivariate normaility test.

4.1.1 MANOVA

In order to investigate whether respondents with greater experience has different opinions on various groups of questions, multivariate analysis of variance (herein after – MANOVA) was performed. Descriptive statistics – mean and standard deviation – for different groups of experience (UQC1) were established (see tables 4-7).

Multivariate tests were applied: Pillai, Wilks, Hotelling-Lawley, Roy. All of which showed that some mean vectors differ statistically significantly ($p < 0.05$). Results show that respondents with less experience on quality criteria application, are more likely to say that quality criteria application might end unsuccessfully, compared to application of lowest price criterion (see table 4). Respondents with less experience on quality criteria application, are more likely to say that they lack knowledge in the field of public procurement and legal acts regulating construction sector (see table 5). Respondents with less experience on quality criteria application, are more likely to say that quality criteria application is complex, difficult more expensive (see table 6).

4.2 Exploratory Factor Analysis

Exploratory factor analysis (hereinafter – EFA), that is used to determine the factor structure of a measure, was performed for testing the validity of the scale items used in measuring the constructs.

UQC1	m_{EP1}	sd_{EP1}	m_{EP2}	sd_{EP2}	m_{EP3}	sd_{EP3}	N
1	3.150	0.717	3.166	0.730	3.179	0.639	295
2	2.809	0.943	2.697	0.829	2.742	0.851	172
3	2.545	1.368	2.273	0.905	2.636	1.286	23

Table 4: Descriptive statistics of EP

UQC1	m_{K1}	sd_{K1}	m_{K2}	sd_{K2}	N
1	3.256	1.110	3.565	1.105	295
2	2.831	1.017	3.067	1.158	172
3	2.091	0.944	2.455	1.508	23

Table 5: Descriptive statistics of K

UQC1	m_{CQC1}	sd_{CQC1}	m_{CQC2}	sd_{CQC2}	m_{CQC3}	sd_{CQC3}	m_{CQC4}	sd_{CQC4}	m_{CQC5}	sd_{CQC5}
1	3.090	0.943	3.110	0.912	3.591	0.810	3.784	0.870	3.648	0.846
2	3.006	0.971	2.927	1.014	3.416	0.924	3.640	0.911	3.382	0.974
3	2.727	0.786	2.636	0.674	3.455	0.934	3.182	0.982	2.636	1.120

Table 6: Descriptive statistics of CQC

UQC1	m_{C1}	sd_{C1}	m_{C2}	sd_{C2}	m_{C3}	sd_{C3}	m_{C4}	sd_{C4}	N
1	3.213	0.801	3.306	0.868	3.213	0.722	3.252	0.759	295
2	3.298	0.786	3.264	0.928	3.202	0.798	3.034	0.743	172
3	3.273	1.009	3.091	1.044	2.909	1.044	3.545	0.820	23

Table 7: Descriptive statistics of C

A principal Component Analysis (hereinafter – PCA), that includes correlated variables in order to reduce the amount of variables and with fewer variables explain the same amount of variance, was conducted on the 17 scale items using the varimax rotation method. Kaiser-Meyer-Olkin (hereinafter) measure and Bartlett's Test of Sphericity were computed to determine how suited collected data is for factor analysis. KMO measure of sampling adequacy value of 0.74 is above the acceptable level of 0.5. P-value of Bartlett's Test of Sphericity is less than 0.05 therefore null hypothesis that the variables are orthogonal, i.e. not correlated, is rejected. Correlation plot of the data has been visualized (see plot 1). KMO and Bartlett's Test of Sphericity results shows that factor analysis is appropriate. Scree plot was used to determine the number of factors (see figure 2). Scree plot shows that the first five eigenvalues are larger than all the others and, therefore supports a five factor solution.

All communalities (proportion of variable variance that can be explained by factors) are sufficiently large ($h2 > 0.20$) (see table 8), meaning that extracted factors explain sufficient amount of each variable's variability.

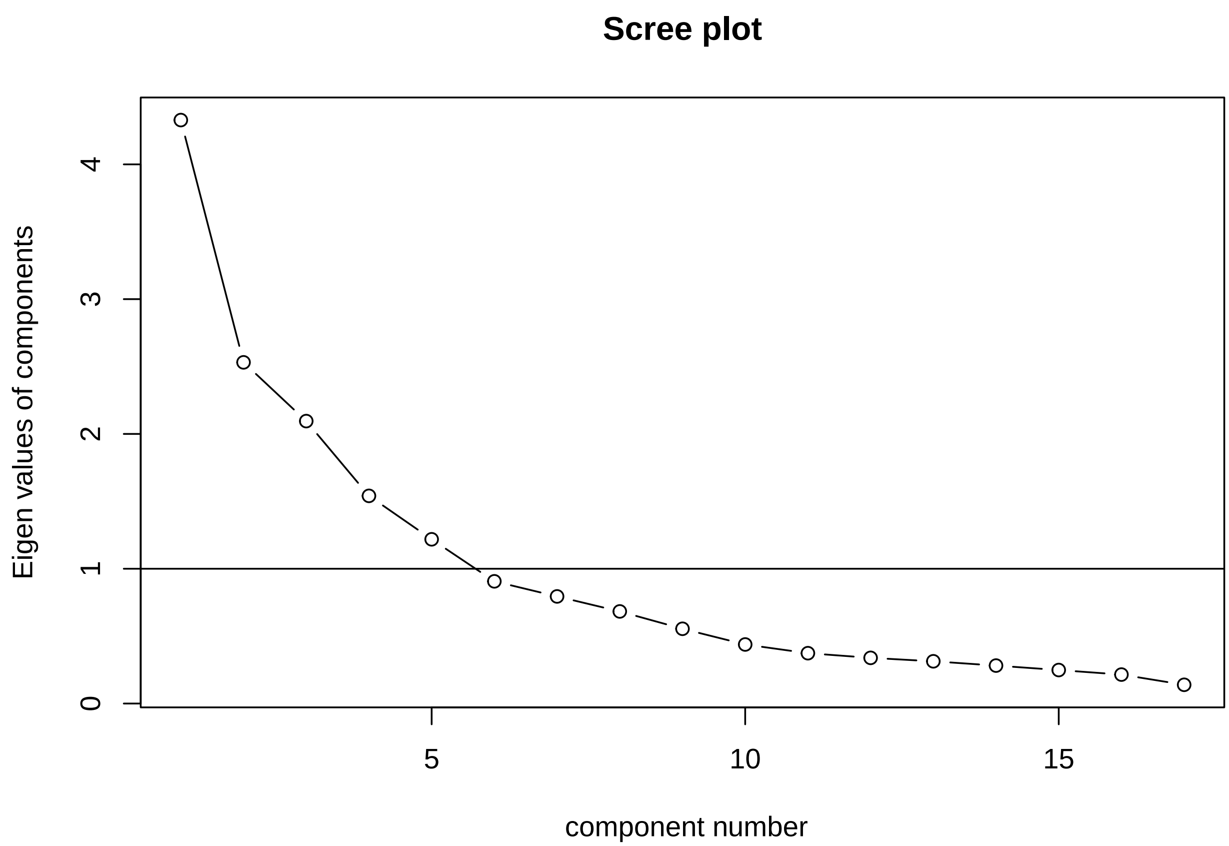

Figure 2: Scree plot.

	Item	RC1	RC3	RC2	RC5	RC4	h2	u2
CQC3	6	0.82					0.63	0.37
CQC4	7	0.75					0.56	0.44
CQC2	5	0.74					0.60	0.40
CQC1	4	0.73					0.64	0.36
CQC5	3	0.52					0.40	0.60
UQC1	8		0.90				0.85	0.15
UQC2	9		0.88				0.78	0.22
UQC3	10		0.80				0.68	0.32
C1	14			0.84			0.71	0.29
C2	15			0.84			0.71	0.29
C3	16			0.68			0.53	0.47
C4	17			0.66			0.50	0.50
EP3	13				0.89		0.82	0.18
EP2	12				0.87		0.79	0.21
EP1	11				0.84		0.75	0.25
K1	1					0.88	0.80	0.20
K2	2					0.87	0.77	0.23

Table 8: Standardized loadings (pattern matrix) based upon correlation matrix.

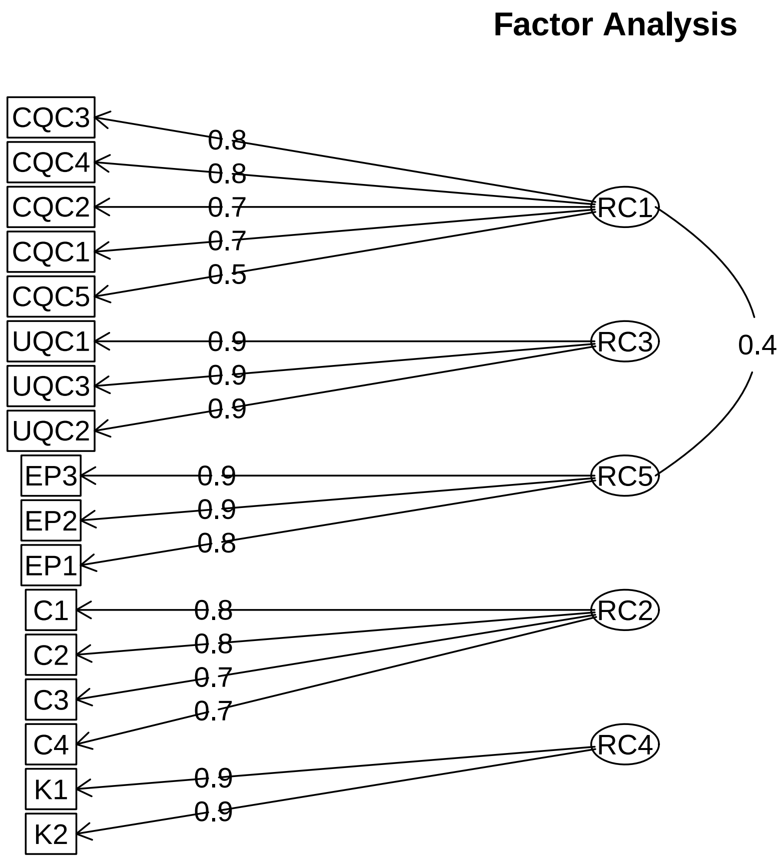

Figure 3: Principal component analysis.

Five factors explain 67.7488 % total variance ($\sim$ 5 factors explain 67.8 % variability in variables) (see table 9). The first factor (RC1) - complexity of quality criteria, second factor (RC2) - competition, third factor (RC3) - usage of quality criteria, fourth factor (RC4) - knowledge, fifth factor (RC5) - end of procedures.

	PC1	PC2	PC3	PC4	PC5
SS loadings	4.2845710	2.4694011	2.0247818	1.5394089	1.1991330
Proportion Var	0.2520336	0.1452589	0.1191048	0.0905535	0.0705372
Cumulative Var	0.2520336	0.3972925	0.5163973	0.6069508	0.6774880
Proportion Explained	0.3720119	0.2144081	0.1758036	0.1336606	0.1041158
Cumulative Proportion	0.3720119	0.5864200	0.7622235	0.8958842	1.0000000

Table 9: Vaccounted.

4.3 Structural equation model

Structural equation modelling approach was adopted. All parameters of latent variables were statistically significant (p-value < 0.05). Five latent variables with statistically significant parameters were created for the model, that corresponds to the groups of questions defined in the beginning and corresponds to the results of PCA (see table 10).

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
UQC =∼						
UQC1	1.000				0.241	0.450
UQC2	0.910	0.092	9.937	0.000	0.219	0.363
UQC3	0.722	0.075	9.655	0.000	0.174	0.413
C =∼						
C1	1.000				0.473	0.592
C2	1.132	0.089	12.736	0.000	0.535	0.600
C3	1.003	0.128	7.856	0.000	0.474	0.626
C4	1.021	0.130	7.849	0.000	0.483	0.634
K =∼						
K1	1.000				0.869	0.790
K2	1.049	0.138	7.581	0.000	0.911	0.784
CQC =∼						
CQC1	1.000				0.643	0.678
CQC2	0.907	0.062	14.660	0.000	0.583	0.615
CQC3	0.804	0.086	9.356	0.000	0.517	0.604
CQC4	0.779	0.088	8.878	0.000	0.501	0.563
CQC5	0.864	0.090	9.586	0.000	0.555	0.606
EP =∼						
EP1	1.000				0.634	0.755
EP2	1.058	0.058	18.149	0.000	0.671	0.831
EP3	1.078	0.058	18.730	0.000	0.683	0.889

Table 10: Latent Variables.

All parameters of regressions were also statistically significant, except for parameter UQC, which was not statistically significant (p-value $= 0.1 > 0.05$) in regression of CQC, but despite the result, this regressor was left in the final model. Measures sucha as The Root Mean Square Error of Approximation (RMSEA), The Comparative Fit Index (CFI), The Goodness of Fit (GFI) and The Standardized Root Mean Square Residual (SRMR). RMSEA measure is equal to 0.057 and is less that 0.1 (represents good fit). CFI, which compares the fit of a target model to the fit of an independent, or null, model, is equal to 0.951 and is greater than 0.9, which also represents good fit. GFI value of constructed model is equal to 0.941 and is greater than 0.9, SRMR come to $0.046 < 0.8$. All of the mentioned measures suggests a good fit.

Model (see figure 4) suggests that usage of quality criteria would fully mediate competitiveness, knowledge, end of procedures and the complexity of quality criteria. Indices did not suggests that there is direct relations between end of procedures and knowledge or competitiveness, complexity of quality criteria and competitiveness.

Results show that lack of knowledge, positive rating of competitiveness and greater acceptance that application of quality criteria is more likely to end the procedures unsuccessfully, has direct and negative effect on usage of quality criteria in public procurement of construction sector. Opinion on end of procedures has a stronger influence on usage of quality criteria (β = -0.257) than knowledge (β = -0.140) or competitiveness (β = -0.121).

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
UQC ∼						
K	-0.140	0.032	-4.360	0.000	-0.503	-0.503
C	-0.121	0.051	-2.356	0.018	-0.237	-0.237
EP	-0.257	0.064	-3.986	0.000	-0.675	-0.675
EP ∼						
CQC	0.768	0.142	5.410	0.000	0.779	0.779
CQC ∼						
K	0.524	0.201	2.613	0.009	0.708	0.708
UQC	1.639	1.018	1.609	0.108	0.615	0.615

Table 11: Regressions.

Lack of qualifications in the field of public procurement (K1) and of legal acts regulating construction and technical aspects related to construction (K2), decreases usage of quality criteria in construction sector procurement. This result corresponds to theory, that application of quality criteria requires additional knowledge, information.

Willingness to agree, that competition in construction sector has been increasing (C3), there is enough contractors participating in public procurement of new construction works (C1), reconstruction, repair, etc. works (C2) and that the application of quality criteria increase competitiveness of procurement in construction sector (C4), decreases usage of quality criteria in construction sector procurement. This relationship is doubtful, because in reference to literature, proper application of quality criteria could possibly increase participation of contractors, which would be desirable result, but increased competition would mean longer and more difficult procedures, because there would be more bids that would require evaluation.

Greater acceptance, that application of quality criteria would end in more terminated procedures (EP1), procedures that ends because of not receiving any offers (EP2) and procedures that ends because all applications are rejected (EP3), decreases the usage of quality criteria in construction sector procurement. This relationship, based on literature is fair. More respondent think implementing quality criteria is going to end procedures unsuccessfully, less motivation they have to use them. If procedures are terminated, that would mean, that contracting authority has to conduct new procedures again, which prolongs the process even more, because application of quality criteria in principle already means longer procedures.

Results also show that greater acceptance that application of quality criteria is more complex, compared to procedures when lowest price criterion is used, has direct and positive effect ($\beta = 0.768$) on view of affect that application of quality criteria has on end of procedures.

Greater acceptance, that applying quality criteria will make contract execution more difficult (CQC1), difficult to ensure proper supervision of contract execution (CQC2), that it is difficult to assess the economic benefits of quality criteria (CQC3), it is difficult to assess which quality criteria may be the most important depending on the construction site (CQC4) and application of quality criteria will increase the prices (CQC5), increases acceptance that usage of quality criteria would end the procedures more unsuccessfully - without conducting a contract. Received result shows that complexity of the application also affects the respondents view on the final result - more difficult, more likely to

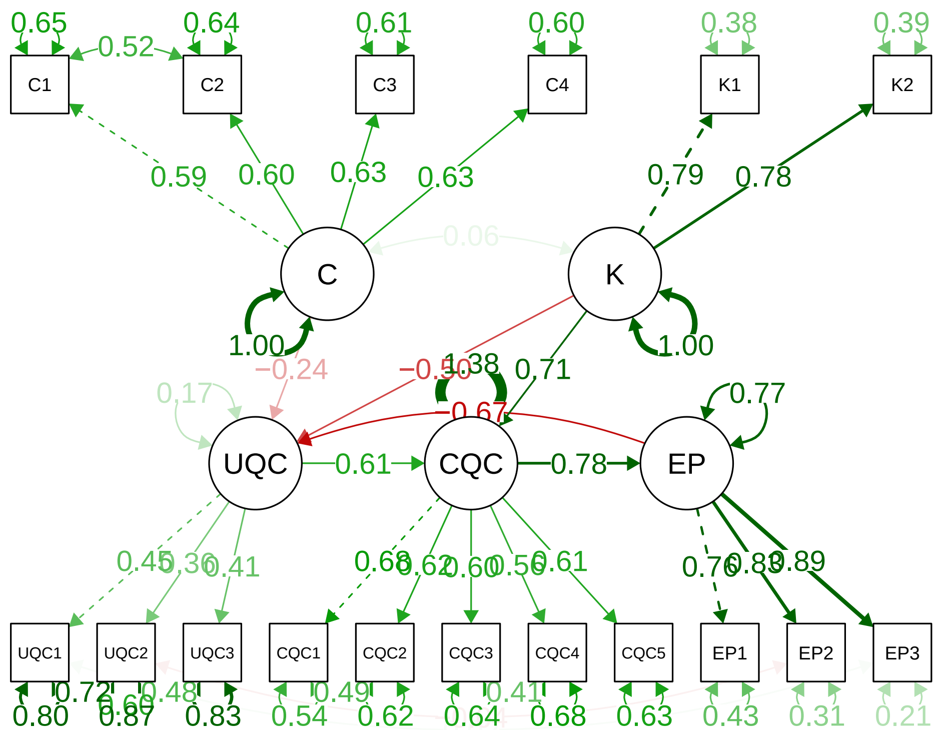

Figure 4: Result of SEM analysis

fail.

Results show that lack of knowledge and greater usage of quality criteria, has direct and positive effect on view of complexity of quality criteria. Usage of quality criteria has a stronger influence on view of complexity ($\beta = 1.639$) than knowledge ($\beta = 0.524$).

Greater lack of qualifications in the field of public procurement (K1) and of legal acts regulating construction and technical aspects related to construction (K2), increases the acceptance, that conducting procedures, that applies quality criteria as evaluation tool, is complicated.

More experience of using quality criteria (UQC1), performing simulations (UQC2), applying environmental criteria (UQC3), increases acceptance that application of quality criteria is complicated. This relationship reflects on how complicated procedures are. Respondents with more experience knows, that procedures requires a lot of research, time, and that not every criterion is beneficial to all projects.

5 Conclusions

Conducted literature review showed that the application of quality criteria in public procurement of construction sector and in general has not only advantages, but also disadvantages. Knowledge about tools applied, concerns about their impact on the final result, availability of contractors may influence the decision to apply them. Application of it not only can bring more quality, economic benefit, but it can also make the whole process more convoluted, longer.

Exploratory factor analysis on the data of conducted survey showed that factor analysis is appropriate – Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.74 (greater that acceptable level of 0.5), Bartlett's Test of Sphericity is significant (p-value < 0.05). Based on scree plot, first five eigenvalues are larger than all others. Five factors explain 67.8 % of total variance.

Structural equation modelling approach was applied and measures for the final model (see figure 4), such as Root Mean Square Error of Approximation (RMSEA) and Comparative Fit Index (CFI) indicated a good fit, respectively 0.057 (less than 0.1) and 0.951 (greater than 0.9). Goodness of Fit (GFI) and Standardized Root Mean Square Residual (SRMR) measures also suggested a good fit.

Structural equation modelling analysis results show that not only lack of knowledge on public procurement system, quality criteria or belief that by applying them less likely procedures will be successful, but also increase in competition in construction sector decreases usage of quality criteria – contracting authorities are less likely to apply them in their procurement of construction sector. Meaning that not only lack of information can stop contracting authorities from using quality criteria, but also avoidance of longer, possibly unsuccessful procedures, more complicated evaluation process.

On the other hand, lack of knowledge in public procurement and greater experience in using them, has direct and positive effect on view of complexity of quality criteria. This shows that the application of quality criteria is a complex process. View on complexity of quality criteria has direct and positive effect on view of end of procedures while applying them, meaning more complicated procedures are while using quality criteria, more authorities are willing to think that these procedures might end unsuccessfully.

On a whole, although quality criteria can lead to more economically beneficial solutions, results offer conclusion, that the whole process of procedures in public procurement of construction sector becomes much more complicated, requires more administrative costs, knowledge not only on quality criteria, but also on public procurement in general, and that in most cases ends with procedures that do not apply quality criteria.

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[7] Natasha K. Bowen, Shenyang Guo. Structural Equation Modeling. 2012

[8] Jolien Grandia. Finding the missing link: Examining the mediating role of sustainable public procurement behaviour. 2016

6 Appendix A

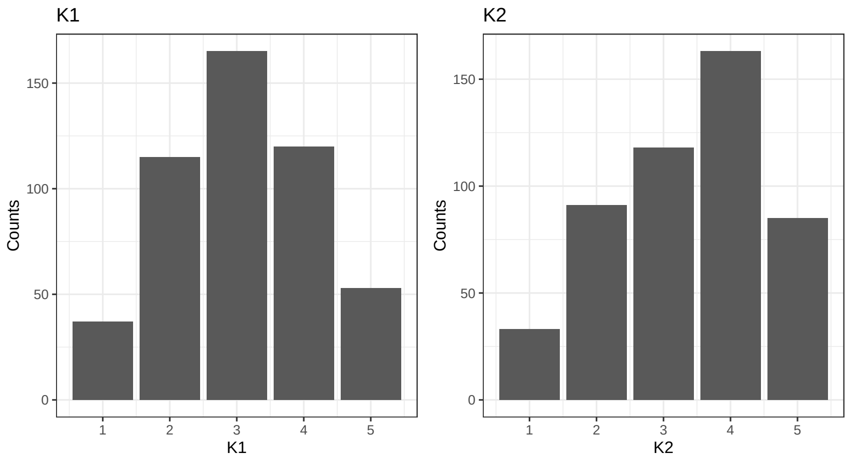

Figure 5: Knowledge variables.

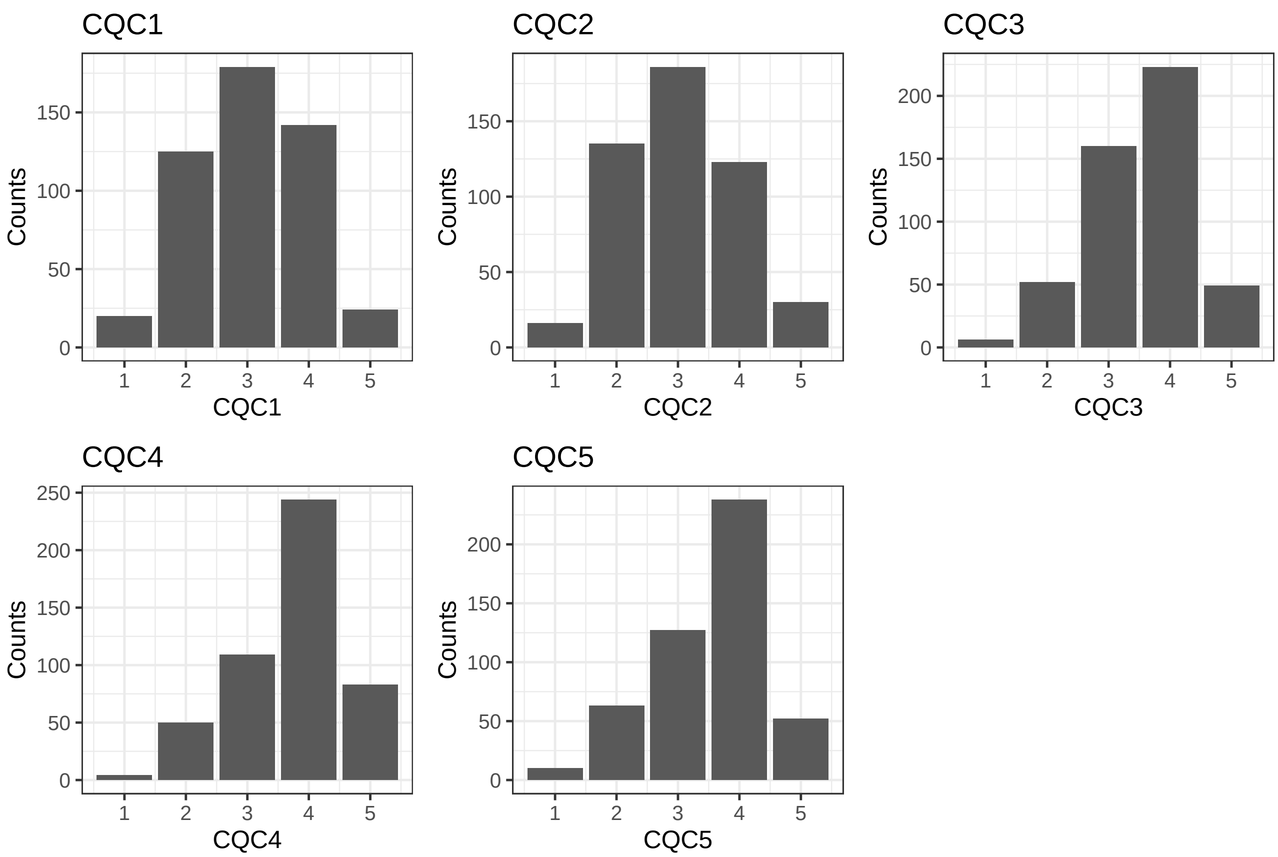

Figure 6: Complexity of quality criteria variables.

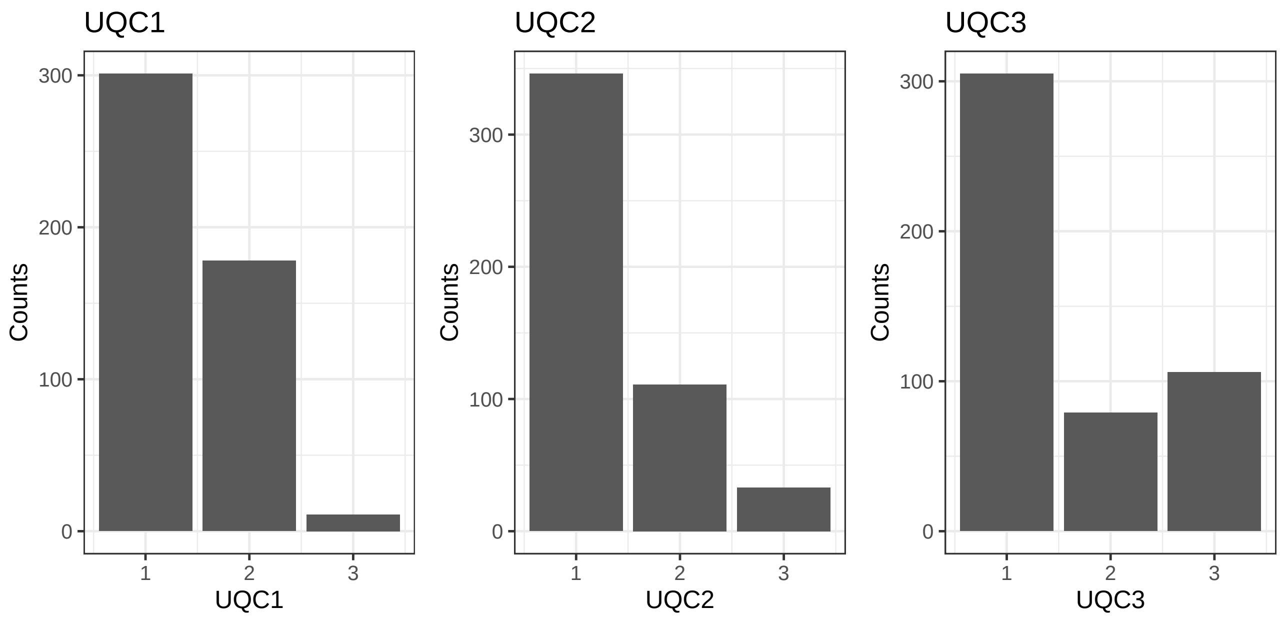

Figure 7: Usage of quality criteria variables.

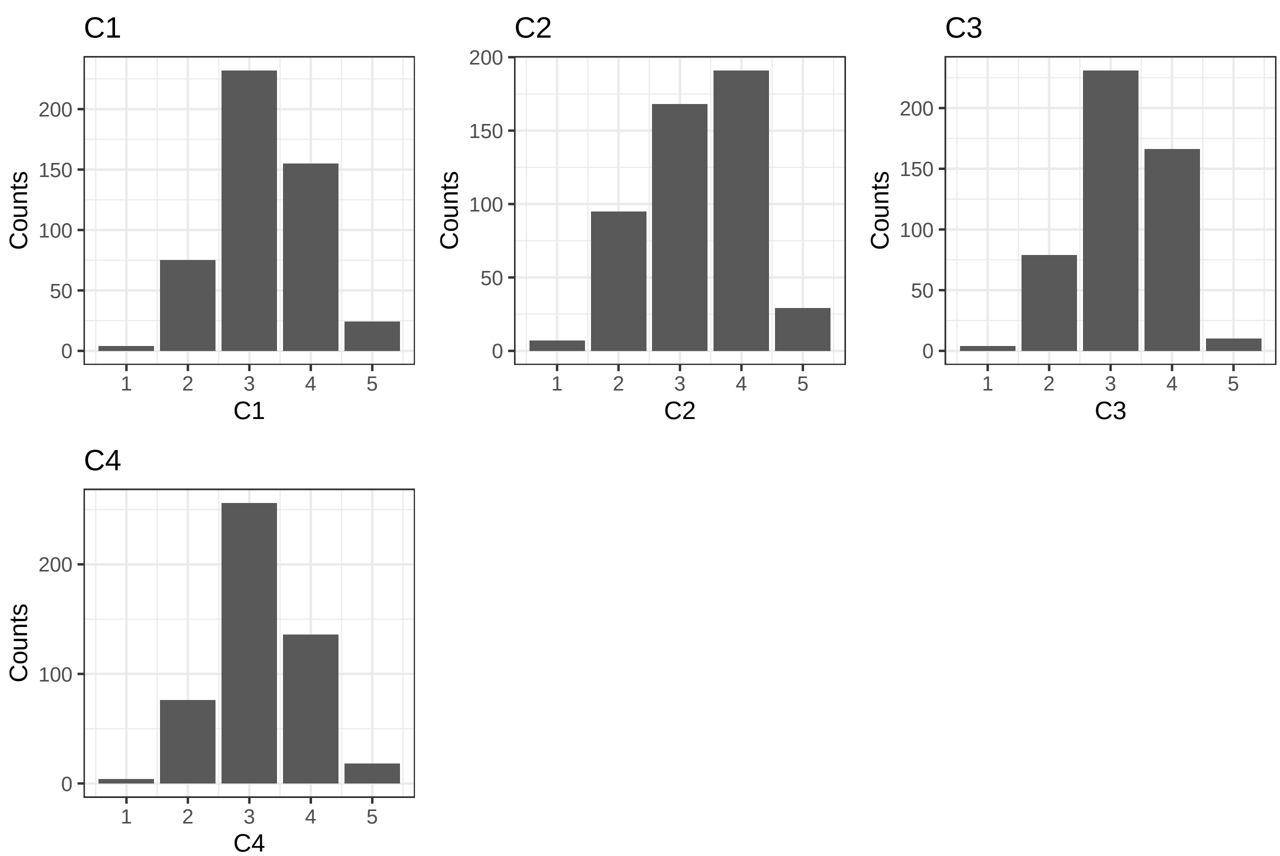

Figure 8: Competition variables.

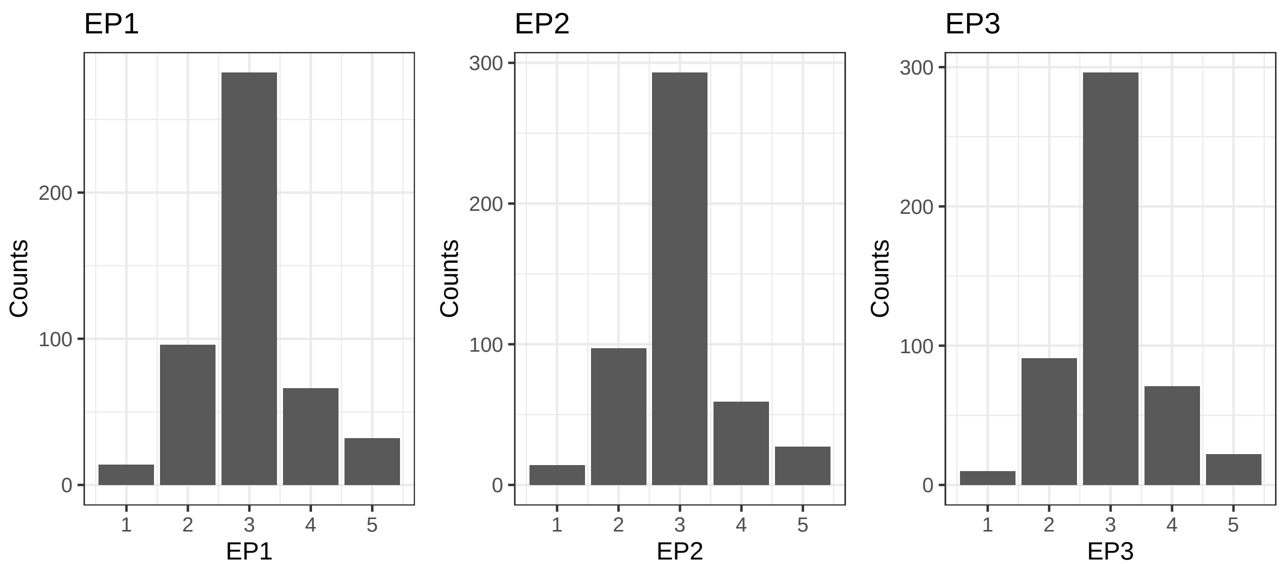

Figure 9: End of procedures variables.

7 Code

```
#Exploratory Data Analysis
#Load & View the Data
#load data of survey
data1 <- read_excel(QCS_Data)
#Dismiss unnecessary columns
data2 <- data1[,c(-1, -2,-19, -20, -21, -22, -23)]

#view first six rows of surveys dataset
head(data2)
# A tibble: 6 × 17
     K1    K2  CQC5  CQC1  CQC2  CQC3  CQC4  UQC1  UQC2  UQC3   EP1   EP2   EP3    C1    C2
  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1     2     4     2     2     4     4     4     2     3     3     3     3     3     4     4
2     3     3     4     3     3     4     3     1     1     1     3     3     3     4     4
3     3     3     2     2     2     3     3     2     2     2     2     2     2     3     5
4     4     4     3     3     3     4     4     1     1     1     3     3     3     5     5
5     1     1     5     4     3     5     5     3     1     1     5     4     5     4     4
6     2     2     3     3     3     3     3     2     2     3     2     2     2     4     4
# ... with 2 more variables: C3 <dbl>, C4 <dbl>


> #summarizing dataset
> summary(data2)
       K1              K2             CQC5            CQC1            CQC2      
 Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
 1st Qu.:2.000   1st Qu.:2.000   1st Qu.:3.000   1st Qu.:2.000   1st Qu.:2.000  
 Median :3.000   Median :4.000   Median :4.000   Median :3.000   Median :3.000  
 Mean   :3.076   Mean   :3.359   Mean   :3.529   Mean   :3.051   Mean   :3.033  
 3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:4.000  
 Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000  
      CQC3            CQC4            UQC1            UQC2            UQC3      
 Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
 1st Qu.:3.000   1st Qu.:3.000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000  
 Median :4.000   Median :4.000   Median :1.000   Median :1.000   Median :1.000  
 Mean   :3.524   Mean   :3.718   Mean   :1.408   Mean   :1.361   Mean   :1.594  
 3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:2.000  
 Max.   :5.000   Max.   :5.000   Max.   :3.000   Max.   :3.000   Max.   :3.000  
      EP1             EP2             EP3              C1              C2       
 Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
```

```
 1st Qu.:3.000   1st Qu.:3.000   1st Qu.:3.000   1st Qu.:3.000   1st Qu.:3.000
 Median :3.000   Median :3.000   Median :3.000   Median :3.000   Median :3.000
 Mean   :3.012   Mean   :2.976   Mean   :3.008   Mean   :3.245   Mean   :3.286
 3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.:4.000   3rd Qu.:4.000
 Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000
       C3               C4
 Min.   :1.000   Min.   :1.00
 1st Qu.:3.000   1st Qu.:3.00
 Median :3.000   Median :3.00
 Mean   :3.202   Mean   :3.18
 3rd Qu.:4.000   3rd Qu.:4.00
 Max.   :5.000   Max.   :5.00

> #display rows and columns
> dim(data2)
[1] 490  17


#Histograms

K1plot<-ggplot(data.frame(data2$K1), aes(x=data2$K1))+
  geom_bar()+
  labs(x="K1", y="Counts", title = "K1")+
  theme_bw()

K2plot<-ggplot(data.frame(data2$K2), aes(x=data2$K2))+
  geom_bar()+
  labs(x="K2", y="Counts", title = "K2")+
  theme_bw()

grid.arrange(K1plot, K2plot, ncol=2)

UQC1plot<-ggplot(data.frame(data2$UQC1), aes(x=data2$UQC1))+
  geom_bar()+
  labs(x="UQC1", y="Counts", title = "UQC1")+
  theme_bw()

UQC2plot<-ggplot(data.frame(data2$UQC2), aes(x=data2$UQC2))+
  geom_bar()+
  labs(x="UQC2", y="Counts", title = "UQC2")+
  theme_bw()
```

```
UQC3plot<-ggplot(data.frame(data2$UQC3), aes(x=data2$UQC3))+
  geom_bar()+
  labs(x="UQC3", y="Counts", title = "UQC3")+
  theme_bw()

grid.arrange(UQC1plot, UQC2plot, UQC3plot, ncol=3)


CQC1plot<-ggplot(data.frame(data2$CQC1), aes(x=data2$CQC1))+
  geom_bar()+
  labs(x="CQC1", y="Counts", title = "CQC1")+
  theme_bw()

CQC2plot<-ggplot(data.frame(data2$CQC2), aes(x=data2$CQC2))+
  geom_bar()+
  labs(x="CQC2", y="Counts", title = "CQC2")+
  theme_bw()

CQC3plot<-ggplot(data.frame(data2$CQC3), aes(x=data2$CQC3))+
  geom_bar()+
  labs(x="CQC3", y="Counts", title = "CQC3")+
  theme_bw()

CQC4plot<-ggplot(data.frame(data2$CQC4), aes(x=data2$CQC4))+
  geom_bar()+
  labs(x="CQC4", y="Counts", title = "CQC4")+
  theme_bw()

CQC5plot<-ggplot(data.frame(data2$CQC5), aes(x=data2$CQC5))+
  geom_bar()+
  labs(x="CQC5", y="Counts", title = "CQC5")+
  theme_bw()

grid.arrange(CQC1plot, CQC2plot, CQC3plot, CQC4plot, CQC5plot, nrow=2, ncol=3)


C1plot<-ggplot(data.frame(data2$C1), aes(x=data2$C1))+
  geom_bar()+
  labs(x="C1", y="Counts", title = "C1")+
  theme_bw()
```

```
C2plot<-ggplot(data.frame(data2$C2), aes(x=data2$C2))+
  geom_bar()+
  labs(x="C2", y="Counts", title = "C2")+
  theme_bw()

C3plot<-ggplot(data.frame(data2$C3), aes(x=data2$C3))+
  geom_bar()+
  labs(x="C3", y="Counts", title = "C3")+
  theme_bw()

C4plot<-ggplot(data.frame(data2$C4), aes(x=data2$C4))+
  geom_bar()+
  labs(x="C4", y="Counts", title = "C4")+
  theme_bw()

grid.arrange(C1plot, C2plot, C3plot, C4plot, nrow=2, ncol=3)


EP1plot<-ggplot(data.frame(data2$EP1), aes(x=data2$EP1))+
  geom_bar()+
  labs(x="EP1", y="Counts", title = "EP1")+
  theme_bw()

EP2plot<-ggplot(data.frame(data2$EP2), aes(x=data2$EP2))+
  geom_bar()+
  labs(x="EP2", y="Counts", title = "EP2")+
  theme_bw()

EP3plot<-ggplot(data.frame(data2$EP3), aes(x=data2$EP3))+
  geom_bar()+
  labs(x="EP3", y="Counts", title = "EP3")+
  theme_bw()

grid.arrange(EP1plot, EP2plot, EP3plot, ncol=3)


#count total missing values in each column
sapply(data2, function(x) sum(is.na(x)))

#MANOVA
```

```
> data2 <- as.data.frame(data2)
> res.man <- manova(cbind(CQC1, CQC2, CQC3, CQC4, CQC5) ~ UQC1, data = data2)

> t_descriptive_g<- data2 %>% group_by(UQC1) %>%
+   summarise(mean_CQC1=mean(CQC1), stand.D_CQC1 = sd(CQC1),
+             mean_CQC2=mean(CQC2), stand.D_CQC2=sd(CQC2),
+             mean_CQC3=mean(CQC3), stand.D_CQC3=sd(CQC3),
+             mean_CQC4=mean(CQC4), stand.D_CQC4=sd(CQC4),
+             mean_CQC5=mean(CQC5), stand.D_CQC5=sd(CQC5),
+             N=n())
> kable(round((t_descriptive_g), digits = 3))


| UQC1| mean_CQC1| stand.D_CQC1| mean_CQC2| stand.D_CQC2| mean_CQC3| stand.D_CQC3|
 mean_CQC4| stand.D_CQC4| mean_CQC5| stand.D_CQC5|   N|
|----:|---------:|------------:|---------:|------------:|---------:|------------:|
---------:|------------:|---------:|------------:|---:|
|    1|     3.090|        0.943|     3.110|        0.912|     3.591|        0.810|
 3.784|        0.870|     3.648|        0.846| 295|
|    2|     3.006|        0.971|     2.927|        1.014|     3.416|        0.924|
 3.640|        0.911|     3.382|        0.974| 172|
|    3|     2.727|        0.786|     2.636|        0.674|     3.455|        0.934|
 3.182|        0.982|     2.636|        1.120|  23|
> #Multivariate tests
> summary(res.man, intercept=TRUE)
             Df  Pillai approx F num Df den Df    Pr(>F)
(Intercept)   1 0.96568  2723.93      5    484 < 2.2e-16 ***
UQC1          1 0.04674     4.75      5    484  0.000304 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> # Or use other tests
> summary(res.man, intercept=TRUE, test="Wilks")
             Df   Wilks approx F num Df den Df    Pr(>F)
(Intercept)   1 0.03432  2723.93      5    484 < 2.2e-16 ***
UQC1          1 0.95326     4.75      5    484  0.000304 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man, intercept=TRUE, test="Hotelling")
             Df Hotelling-Lawley approx F num Df den Df    Pr(>F)
```

```
(Intercept)   1           28.140  2723.93      5    484 < 2.2e-16 ***
UQC1          1            0.049     4.75      5    484  0.000304 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man, intercept=TRUE, test="Roy")
             Df    Roy approx F num Df den Df    Pr(>F)
(Intercept)   1 28.140  2723.93      5    484 < 2.2e-16 ***
UQC1          1  0.049     4.75      5    484  0.000304 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
#---------------------------------------------------------------------------------
> #EP
> res.man1 <- manova(cbind(EP1, EP2, EP3) ~ UQC1, data = data2)
> #Descriptive statistics
> t_descriptive_g1<- data2 %>% group_by(UQC1) %>%
+   summarise(mean_EP1=mean(EP1), stand.D_EP1 = sd(EP1),
+             mean_EP2=mean(EP2), stand.D_EP2=sd(EP2),
+             mean_EP3=mean(EP3), stand.D_EP3=sd(EP3),
+             N=n())
>
> kable(round((t_descriptive_g1), digits = 3))


| UQC1| mean_EP1| stand.D_EP1| mean_EP2| stand.D_EP2| mean_EP3| stand.D_EP3|   N|
|----:|--------:|-----------:|--------:|-----------:|--------:|-----------:|---:|
|    1|    3.150|       0.717|    3.166|       0.730|    3.179|       0.639| 295|
|    2|    2.809|       0.943|    2.697|       0.829|    2.742|       0.851| 172|
|    3|    2.545|       1.368|    2.273|       0.905|    2.636|       1.286|  23|
>
> #Multivariate tests
> summary(res.man1, intercept=TRUE)
             Df  Pillai approx F num Df den Df    Pr(>F)
(Intercept)   1 0.95116   3155.2      3    486 < 2.2e-16 ***
UQC1          1 0.09950     17.9      3    486 4.929e-11 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man1, intercept=TRUE, test="Wilks")
             Df   Wilks approx F num Df den Df    Pr(>F)
```

```
(Intercept)   1 0.04884   3155.2      3    486 < 2.2e-16 ***
UQC1          1 0.90050     17.9      3    486 4.929e-11 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man1, intercept=TRUE, test="Hotelling")
             Df Hotelling-Lawley approx F num Df den Df    Pr(>F)
(Intercept)   1          19.4766   3155.2      3    486 < 2.2e-16 ***
UQC1          1           0.1105     17.9      3    486 4.929e-11 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man1, intercept=TRUE, test="Roy")
             Df     Roy approx F num Df den Df    Pr(>F)
(Intercept)   1 19.4766   3155.2      3    486 < 2.2e-16 ***
UQC1          1  0.1105     17.9      3    486 4.929e-11 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
#-------------------------------------------------------------------------------------
> #K
> res.man2 <- manova(cbind(K1, K2) ~ UQC1, data = data2)
> #Descriptive statistics
> t_descriptive_g2<- data2 %>% group_by(UQC1) %>%
+   summarise(mean_K1=mean(K1), stand.D_K1 = sd(K1),
+             mean_K2=mean(K2), stand.D_K2=sd(K2),
+             N=n())
> kable(round((t_descriptive_g2), digits = 3))


| UQC1| mean_K1| stand.D_K1| mean_K2| stand.D_K2|   N|
|----:|-------:|----------:|-------:|----------:|---:|
|    1|   3.256|      1.110|   3.565|      1.105| 295|
|    2|   2.831|      1.017|   3.067|      1.158| 172|
|    3|   2.091|      0.944|   2.455|      1.508|  23|
> #Multivariate tests
> summary(res.man2, intercept=TRUE)
             Df  Pillai approx F num Df den Df    Pr(>F)
(Intercept)   1 0.91453  2605.61      2    487 < 2.2e-16 ***
UQC1          1 0.06585    17.17      2    487  6.25e-08 ***
Residuals   488
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man2, intercept=TRUE, test="Wilks")
             Df   Wilks approx F num Df den Df    Pr(>F)
(Intercept)   1 0.08547  2605.61      2    487 < 2.2e-16 ***
UQC1          1 0.93415    17.17      2    487  6.25e-08 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man2, intercept=TRUE, test="Hotelling")
             Df Hotelling-Lawley approx F num Df den Df    Pr(>F)
(Intercept)   1          10.7007  2605.61      2    487 < 2.2e-16 ***
UQC1          1           0.0705    17.17      2    487  6.25e-08 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(res.man2, intercept=TRUE, test="Roy")
             Df     Roy approx F num Df den Df    Pr(>F)
(Intercept)   1 10.7007  2605.61      2    487 < 2.2e-16 ***
UQC1          1  0.0705    17.17      2    487  6.25e-08 ***
Residuals   488
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
#--------------------------------------------------------------------------------
> #C
> res.man3 <- manova(cbind(C1, C2, C3, C4) ~ UQC1, data = data2)
> #Descriptive statistics
> t_descriptive_g3<- data2 %>% group_by(UQC1) %>%
+   summarise(mean_C1=mean(C1), stand.D_C1 = sd(C1),
+             mean_C2=mean(C2), stand.D_C2=sd(C2),
+             mean_C3=mean(C3), stand.D_C3=sd(C3),
+             mean_C4=mean(C4), stand.D_C4=sd(C4),
+             N=n())
> kable(round((t_descriptive_g3),digits = 3))


| UQC1| mean_C1| stand.D_C1| mean_C2| stand.D_C2| mean_C3| stand.D_C3|
 mean_C4| stand.D_C4|   N|
|----:|-------:|----------:|-------:|----------:|-------:|----------:|
-------:|----------:|---:|
|    1|   3.213|      0.801|   3.306|      0.868|   3.213|      0.722|
```

```
   3.252|      0.759| 295|
|    2|   3.298|      0.786|   3.264|      0.928|   3.202|      0.798|
   3.034|      0.743| 172|
|    3|   3.273|      1.009|   3.091|      1.044|   2.909|      1.044|
   3.545|      0.820|  23|
> #Multivariate tests
> summary(res.man3, intercept=TRUE)
             Df  Pillai approx F num Df den Df  Pr(>F)
(Intercept)   1 0.96732   3588.7      4    485 < 2e-16 ***
UQC1          1 0.02137      2.6      4    485 0.03283 *
Residuals   488
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(res.man3, intercept=TRUE, test="Wilks")
             Df   Wilks approx F num Df den Df  Pr(>F)
(Intercept)   1 0.03268   3588.7      4    485 < 2e-16 ***
UQC1          1 0.97863      2.6      4    485 0.03283 *
Residuals   488
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(res.man3, intercept=TRUE, test="Hotelling")
             Df Hotelling-Lawley approx F num Df den Df  Pr(>F)
(Intercept)   1          29.5978   3588.7      4    485 < 2e-16 ***
UQC1          1           0.0218      2.6      4    485 0.03283 *
Residuals   488
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(res.man3, intercept=TRUE, test="Roy")
             Df     Roy approx F num Df den Df  Pr(>F)
(Intercept)   1 29.5978   3588.7      4    485 < 2e-16 ***
UQC1          1  0.0218      2.6      4    485 0.03283 *
Residuals   488
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#Exploratory Factor Analysis

> #Correlation plot
> res <-cor(data2, method = c("pearson"))
> corrplot(res, type = "upper", order = "hclust",
+          tl.col = "black", tl.srt = 45)
```

```
> lowerCor(data2, method = "pearson")
     K1    K2    CQC5  CQC1  CQC2  CQC3  CQC4  UQC1  UQC2  UQC3  EP1   EP2   EP3
K1    1.00
K2    0.62  1.00
CQC5  0.20  0.14  1.00
CQC1  0.18  0.20  0.43  1.00
CQC2  0.15  0.16  0.33  0.70  1.00
CQC3  0.11  0.10  0.36  0.41  0.43  1.00
CQC4  0.12  0.20  0.32  0.36  0.37  0.61  1.00
UQC1 -0.23 -0.24 -0.19 -0.06 -0.11 -0.09 -0.11  1.00
UQC2 -0.21 -0.22 -0.11 -0.04 -0.08 -0.09 -0.16  0.76  1.00
UQC3 -0.21 -0.22 -0.12 -0.07 -0.09 -0.12 -0.09  0.83  0.68  1.00
EP1   0.12  0.18  0.33  0.38  0.37  0.23  0.27 -0.21 -0.19 -0.21  1.00
EP2   0.14  0.10  0.26  0.26  0.25  0.27  0.29 -0.31 -0.25 -0.28  0.62  1.00
EP3   0.11  0.14  0.31  0.28  0.26  0.27  0.30 -0.28 -0.20 -0.30  0.67  0.74  1.00
C1    0.03 -0.03 -0.07  0.00 -0.03 -0.11 -0.03  0.05  0.08  0.01  0.00 -0.08 -0.07
C2   -0.01 -0.07 -0.09 -0.09 -0.08 -0.11 -0.03 -0.03  0.00 -0.01 -0.06 -0.06 -0.13
C3    0.20  0.10 -0.03  0.02  0.03 -0.02 -0.02 -0.03 -0.04 -0.01  0.03  0.03 -0.05
C4    0.00 -0.04 -0.18 -0.11 -0.05 -0.13 -0.19 -0.09 -0.05 -0.11  0.00  0.01 -0.07
   C1    C2    C3    C4
C1  1.00
C2  0.69  1.00
C3  0.38  0.38  1.00
C4  0.37  0.38  0.39  1.00

> #Testing normality and ploting histograms
> mvnout <- mardia(data2)
> ## Shapiro-Wilk Univariate normality test
> mvnout$uv.shapiro #same as apply(data2, 2, shapiro.test)
     W      p-value UV.Normality
K1   0.9164 0       No
K2   0.9031 0       No
CQC5 0.8648 0       No
CQC1 0.8993 0       No
CQC2 0.8984 0       No
CQC3 0.8717 0       No
CQC4 0.8599 0       No
UQC1 0.6631 0       No
UQC2 0.6166 0       No
UQC3 0.6725 0       No
EP1  0.8442 0       No
```

```
EP2  0.8301 0       No
EP3  0.8281 0       No
C1   0.8683 0       No
C2   0.8792 0       No
C3   0.8494 0       No
C4   0.8549 0       No


> ## Mardia Multivariate normality test
> mvnout$mv.test
          Test Statistic p-value Result
1     Skewness 4442.0054       0     NO
2     Kurtosis   31.2168       0     NO
3 MV Normality      <NA>    <NA>     NO


> #Kaiser-Meyer-Olkin measure (OK if KMO > 0.50)
> KMO(data2)
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = data2)
Overall MSA =  0.74
MSA for each item =
  K1   K2 CQC5 CQC1 CQC2 CQC3 CQC4 UQC1 UQC2 UQC3  EP1  EP2  EP3   C1   C2   C3   C4
0.63 0.64 0.84 0.75 0.75 0.76 0.75 0.70 0.82 0.74 0.85 0.78 0.77 0.62 0.65 0.77 0.76
> bart_spher(data2) #Bartlett's test (OK if p < 0.05)

Bartlett's Test of Sphericity

Call: bart_spher(x = data2)

     X2 = 3744.176
     df = 136
p-value < 2.22e-16

> pca0 <- principal(data2, nfactors=17,
+                   rotate="none") ## initial communalities are all 1
> kable(pca0$communality)


|     |  x|
|:----|--:|
```

```
|K1   |  1|
|K2   |  1|
|CQC5 |  1|
|CQC1 |  1|
|CQC2 |  1|
|CQC3 |  1|
|CQC4 |  1|
|UQC1 |  1|
|UQC2 |  1|
|UQC3 |  1|
|EP1  |  1|
|EP2  |  1|
|EP3  |  1|
|C1   |  1|
|C2   |  1|
|C3   |  1|
|C4   |  1|
```

```
> pca <- principal(data2, nfactors=5, rotate="none")
> #Scree plot to determine the number of factors
> kable(pca$communality)
```

```
|     |         x|
|:----|---------:|
|K1   | 0.7981244|
|K2   | 0.7771195|
|CQC5 | 0.3984618|
|CQC1 | 0.6409438|
|CQC2 | 0.5982243|
|CQC3 | 0.6281072|
|CQC4 | 0.5561924|
|UQC1 | 0.8887702|
|UQC2 | 0.7854365|
|UQC3 | 0.8315560|
|EP1  | 0.7508940|
|EP2  | 0.7864725|
|EP3  | 0.8239854|
|C1   | 0.7062752|
|C2   | 0.7094514|
```

```
|C3   | 0.5284522|
|C4   | 0.5052607|

> kable(pca$Vaccounted)


|                      |       PC1|       PC2|       PC3|       PC4|       PC5|
|:---------------------|---------:|---------:|---------:|---------:|---------:|
|SS loadings           | 4.3284393| 2.5310510| 2.0952220| 1.5406673| 1.2183480|
|Proportion Var        | 0.2546141| 0.1488854| 0.1232484| 0.0906275| 0.0716675|
|Cumulative Var        | 0.2546141| 0.4034994| 0.5267478| 0.6173753| 0.6890428|
|Proportion Explained  | 0.3695185| 0.2160756| 0.1788689| 0.1315266| 0.1040103|
|Cumulative Proportion | 0.3695185| 0.5855941| 0.7644631| 0.8959897| 1.0000000|
> VSS.scree(data2, main = "Scree plot")

> pca.v <- kaiser(principal(data2, nfactors=5,
+                            rotate="varimax")) ## with Kaiser normaliz
> print.psych(pca.v, cut = 0.4, sort = TRUE)

Call: NULL
Standardized loadings (pattern matrix) based upon correlation matrix
     item  RC1   RC3   RC5   RC2   RC4   h2   u2
CQC3    6  0.82                         0.63 0.37
CQC4    7  0.75                         0.56 0.44
CQC2    5  0.75                         0.60 0.40
CQC1    4  0.74                         0.64 0.36
CQC5    3  0.52                         0.40 0.60
UQC1    8        0.92                   0.89 0.11
UQC3   10        0.89                   0.83 0.17
UQC2    9        0.88                   0.79 0.21
EP3    13              0.90             0.82 0.18
EP2    12              0.88             0.79 0.21
EP1    11              0.84             0.75 0.25
C1     14                    0.84       0.71 0.29
C2     15                    0.84       0.71 0.29
C3     16                    0.68       0.53 0.47
C4     17                    0.66       0.51 0.49
K1      1                          0.88 0.80 0.20
K2      2                          0.87 0.78 0.22

                       RC1  RC3  RC5  RC2  RC4
```

```
SS loadings           2.74 2.54 2.41 2.33 1.69
Proportion Var        0.16 0.15 0.14 0.14 0.10
Cumulative Var        0.16 0.31 0.45 0.59 0.69
Proportion Explained  0.23 0.22 0.21 0.20 0.14
Cumulative Proportion 0.23 0.45 0.66 0.86 1.00
      RC1   RC3   RC5   RC2   RC4
RC1  1.00 -0.10  0.38 -0.11  0.20
RC3 -0.10  1.00 -0.26 -0.02 -0.18
RC5  0.38 -0.26  1.00 -0.04  0.17
RC2 -0.11 -0.02 -0.04  1.00  0.04
RC4  0.20 -0.18  0.17  0.04  1.00
> fa.diagram(pca.v)

> #SEM Analysis
> model1 = '
+   # measurement model
+     UQC =~ UQC1 + UQC2 + UQC3
+     C =~ C1 + C2 + C3 + C4
+     K =~ K1 + K2
+     CQC =~ CQC1 + CQC2 + CQC3 + CQC4 + CQC5
+     EP =~ EP1 + EP2 + EP3
+
+   # structural model
+     UQC ~ K + C + EP
+     EP ~ CQC
+     CQC ~ K + UQC
+
+   # correlated residuals
+     UQC1 ~~ EP3
+     UQC2 ~~ EP2
+     UQC1 ~~ UQC3
+     UQC2 ~~ UQC1
+     UQC2 ~~ UQC3
+     CQC1 ~~ CQC2
+     CQC3 ~~ CQC4
+     C1 ~~ C2
+ '
> fit1<-sem(model1, data = data
+           # ,sample.cov=cov
+ )
```

```
> summary(fit1, standardized = TRUE)
lavaan 0.6-9 ended normally after 84 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        49

  Number of observations                           490

Model Test User Model:

  Test statistic                               268.217
  Degrees of freedom                               104
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  UQC =~
    UQC1              1.000                               0.252    0.470
    UQC2              0.889    0.090    9.909    0.000    0.224    0.371
    UQC3              1.474    0.105   14.060    0.000    0.371    0.451
  C =~
    C1                1.000                               0.470    0.589
    C2                1.136    0.089   12.707    0.000    0.535    0.599
    C3                1.005    0.128    7.849    0.000    0.473    0.624
    C4                1.033    0.132    7.837    0.000    0.486    0.638
  K =~
    K1                1.000                               0.862    0.784
    K2                1.066    0.144    7.401    0.000    0.918    0.790
  CQC =~
    CQC1              1.000                               0.643    0.679
    CQC2              0.906    0.062   14.658    0.000    0.583    0.615
    CQC3              0.803    0.086    9.352    0.000    0.517    0.603
    CQC4              0.779    0.088    8.878    0.000    0.501    0.563
    CQC5              0.864    0.090    9.590    0.000    0.556    0.607
```

```
  EP =~
    EP1               1.000                               0.631    0.752
    EP2               1.064    0.059   18.140    0.000    0.672    0.832
    EP3               1.083    0.058   18.706    0.000    0.684    0.890

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  UQC ~
    K                -0.134    0.033   -4.090    0.000   -0.460   -0.460
    C                -0.131    0.054   -2.442    0.015   -0.245   -0.245
    EP               -0.276    0.067   -4.135    0.000   -0.692   -0.692
  EP ~
    CQC               0.763    0.140    5.444    0.000    0.778    0.778
  CQC ~
    K                 0.501    0.182    2.753    0.006    0.671    0.671
    UQC               1.523    0.924    1.648    0.099    0.596    0.596

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .UQC1 ~~
   .EP3               0.009    0.006    1.479    0.139    0.009    0.053
 .UQC2 ~~
   .EP2              -0.013    0.010   -1.392    0.164   -0.013   -0.054
 .UQC1 ~~
   .UQC3              0.274    0.040    6.859    0.000    0.274    0.790
   .UQC2              0.189    0.026    7.372    0.000    0.189    0.713
 .UQC2 ~~
   .UQC3              0.256    0.038    6.783    0.000    0.256    0.623
 .CQC1 ~~
   .CQC2              0.257    0.041    6.259    0.000    0.257    0.495
 .CQC3 ~~
   .CQC4              0.207    0.033    6.236    0.000    0.207    0.413
 .C1 ~~
   .C2                0.242    0.037    6.555    0.000    0.242    0.525
  C ~~
    K                 0.022    0.026    0.863    0.388    0.055    0.055

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .UQC1              0.224    0.028    8.086    0.000    0.224    0.780
   .UQC2              0.315    0.028   11.343    0.000    0.315    0.863
```

```
  .UQC3              0.538    0.062    8.729    0.000    0.538    0.796
  .C1                0.417    0.038   10.840    0.000    0.417    0.653
  .C2                0.510    0.048   10.645    0.000    0.510    0.641
  .C3                0.350    0.034   10.368    0.000    0.350    0.611
  .C4                0.344    0.035    9.942    0.000    0.344    0.593
  .K1                0.466    0.100    4.658    0.000    0.466    0.385
  .K2                0.509    0.113    4.498    0.000    0.509    0.376
  .CQC1              0.485    0.048   10.150    0.000    0.485    0.539
  .CQC2              0.559    0.049   11.343    0.000    0.559    0.622
  .CQC3              0.466    0.039   11.914    0.000    0.466    0.636
  .CQC4              0.541    0.043   12.507    0.000    0.541    0.683
  .CQC5              0.530    0.044   12.098    0.000    0.530    0.632
  .EP1               0.306    0.024   12.793    0.000    0.306    0.434
  .EP2               0.201    0.020   10.227    0.000    0.201    0.308
  .EP3               0.123    0.017    7.160    0.000    0.123    0.208
  .UQC               0.014    0.023    0.610    0.542    0.226    0.226
   C                 0.221    0.041    5.333    0.000    1.000    1.000
   K                 0.743    0.119    6.236    0.000    1.000    1.000
  .CQC               0.563    0.176    3.198    0.001    1.360    1.360
  .EP                0.306    0.045    6.822    0.000    0.768    0.768

> #graph_sem(model = fit)
> semPaths(fit1,"std",edge.label.cex=1.1)
> fitMeasures(fit1, c('chisq', 'df', 'pvalue', 'cfi', 'rmsea', 'srmr', 'AIC', 'gfi'))
    chisq        df    pvalue       cfi     rmsea      srmr       aic       gfi
  268.217   104.000     0.000     0.955     0.057     0.046 17186.063     0.941
```