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Mirjana Pejić Bach
University of Zagreb

Jurij Jaklič
University of Ljubljana

Dalia Suša Vugec
University of Zagreb

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Mirjana Pejić Bach
Faculty of Economics and Business, University of Zagreb
Trg J.F. Kennedya 6, 10000 Zagreb, Croatia
www.shortbio.org/mpejic@efzg.hr

Jurij Jaklič
Faculty of Economics, University of Ljubljana
Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia
www.shortbio.org/jurij.jaklic@ef.uni-lj.si

Dalia Suša Vugec
Faculty of Economics and Business, University of Zagreb
Trg J.F. Kennedya 6, 10000 Zagreb, Croatia
www.shortbio.org/dsusa@efzg.hr

Abstract:
Business intelligence is an approach that includes processes and systems for transformation of the raw data into meaningful and useful information which enables effective, systematic and purposeful analysis of an organization and its competitive environment. This paper aims to analyze the impact of the level of business intelligence maturity to organizational performance of the company. Moreover, since there is a rising awareness among practitioners of the role of the organizational culture for the successful functioning of the company, the role of the organizational culture is taken into consideration in this research. In order to meet the aim of the paper, a survey has been conducted. Data has been collected through questionnaires on a sample of 177 Croatian and Slovenian companies and analyzed by means of the cluster analysis. The analysis identified two clusters. The results of the cross-tabulation analysis of the clusters reveal statistically significant differences in terms of the company turnover and dominant organizational culture between them.

Keywords:
business intelligence; business intelligence maturity; organizational performance; organizational culture; cluster analysis.

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1. Introduction

In the new global economy and in the conditions of growing number of data provided by the technology development, business intelligence (BI) can be considered as a central approach for successful management of the relevant business data in order to provide support to the decision-making processes. BI encompasses all processes and systems (e.g. data warehouses, data marts, analytical tools such as reporting tools, ad hoc analytics and OLAP, in-memory analytics, planning, alerts, forecasts, scorecards, data mining) that transform raw data into meaningful and useful information and enable effective, systematic and purposeful analysis of an organization and its competitive environment [1], [2], [3]. It is highly important for organizations to be able to recognize and exploit relevant and important information among enormous amount of data generated in business world each day. Only if BI is used to enhance decision making [4] or to improve business processes [5], it can affect the organization's performance. Therefore, BI can be an important means of competitive advantage for the company, if properly applied and utilized.

One of the ways of measuring the success of BI usage within the company is assessing the BI maturity. Although there is a number of BI maturity models developed over time (e.g. Watson et al. [6], Aho [7], Tan et al. [8]), according to our knowledge, there is no BI maturity model that would be commonly accepted and widely used for researches. Furthermore, most maturity models [9] only address certain aspects of technological maturity or system quality (such as data integration and analytical capabilities) and output quality, which refers to information quality and as such they are not comprehensive.

Besides dealing with the large amounts of information, there is also a rising awareness among practitioners of the role of the organizational culture for the successful functioning of the company. Moreover, this topic is being in the scope of many researchers in the last few decades, resulting in growing body of literature dealing with examining organizational culture and its impact on organizational functioning and performance (e.g. Balthazard et al. [10], Jacobs et al. [11], Naranjo-Valencia et al. [12]).

In the light of organizational performance (OP), current researches also reveal BI to be of a great importance in achieving higher business performance (e.g. Sparks [13], Wieder and Ossimitz [14], Daneshvar Kakhki and Palvia [15]). However, to our best knowledge, there is no research that would investigate the combined impact of both BI and organizational culture to OP. Therefore, the goal of the paper is to analyze the impact of BI to OP and the role of organizational culture in that impact by using cluster analysis for analyzing the data collected through questionnaires.

In order to fulfill the goals of this paper, its structure is as follows. After this introduction, a brief literature review is given, concentrating on previous research of the impact of BI and organizational culture on OP as well as the previous research on the usage of cluster analysis in information systems research. Third part of this paper focuses on the methodology used for this study, providing the overview of the research instrument, sample characteristics and k-means clustering procedure. Fourth part of the paper presents the results of the data analysis, followed by the discussion in the fifth part. At the end, a short conclusion with limitations and plans for future research is presented.

2. Literature review

This section of the paper presents short literature review on previous researches concentrated on the impact of BI on OP and the impact of organizational culture on the usage of information systems and OP. Also, the short overview of the usage of cluster analysis in previous information systems research is presented.

2.1 Previous research about impact of business intelligence on organizational performance

For the purpose of this study and in order to revise previous researches on the impact of BI on OP, the definition of BI given by Moss and Atre [16] has been accepted. They define BI as “an architecture and a collection of integrated operational as well as decision-support applications and databases that provide the business community easy access to business data” [16]. Bosilj Vuksic et al. discuss that integration of BI with other systems in the company [17].

When it comes to the previous researches of the impact of BI on OP, Elbashir et al. [18] emphasize the need of examining that impact on the two levels of performance, which are (1) business process performance and (2) OP, indicating that measuring BI benefits on organizational level can be viewed as a tool for evaluation of the understanding of OP benefits within the company. On the other hand, a number of researches on BI reveal its effects to the OP. For example, Sparks [9] provides empirical confirmation of BI usage resulting in OP benefits. Moreover, Wieder and Ossimitz [14] also deliver evidence of direct and indirect impact of BI to decision support improvements. Based on the secondary data analysis from public companies in the USA, Daneshvar Kakhki and Palvia [15] report positive relationship between the implementation of BI and OP.

Previous research of BI often implies measuring the BI maturity in order to investigate its impact to other aspects of the company. So far, in the field of BI, there has been a number of maturity models developed. Lahrmann et al. [19] conducted a literature review on BI maturity models resulting with an overview of twelve different maturity models developed from 2001 to 2009. This literature review has recently been updated by Raber et al. [20], who propose yet another instrument for measuring BI maturity. For the purpose of this study, the focus is put on the BI maturity model proposed by Dinter [21], as this is one of the most comprehensive and systematic BI maturity models that covers all important aspects, organized in three dimensions: functionality, technology, and organization. Addressing only functionality and technology issues of BI cannot result in improved organizational performance. Pejić Bach et al. [22] show the importance of some organizational factors on BI successful implementation. Therefore, it is crucial that BI maturity model includes also the organizational dimension when used in such a study. The Dinter's model development with the focus on comprehensiveness and was based on an extensive analysis of previously existing models. It is a conceptual BI maturity model based on the original work of Steria Mummert Consulting in cooperation with universities from 2004 which suggests five stages of BI maturity, respectively: (1) individual information, (2) information islands, (3) information integration, (4) information intelligence, and (5) enterprise information management.

2.2 Previous research on the usage of cluster analysis in information systems research

Cluster analysis is a well-known statistic method for analyzing data. It is one of the multivariate statistical methods in which the data structure for grouping multivariate observations in clusters is sought. Therefore, it has been previously used in many studies by numerous authors. Both information systems research and BI research are no exception to that, as it is visible from few examples listed in continuation.

For example, Doherty et al. [23] used cluster analysis for identification of different classes of approach to the application of strategic information systems planning based on ten key planning dimensions. The results of the analysis of 267 responses collected from different companies revealed four clusters indicating four alternative approaches to the strategic information systems planning application [23]. Another example is the work of Wallace et al. [24] who used cluster analysis in analyzing the data collected from 507 software project managers through questionnaires. By employing k-means cluster analysis, they identified the trends in risk dimensions across three clusters, being low, medium and high risk projects [24]. The impact of project scope, sourcing practices and strategic orientation on project risks has been examined as well in the same research [24]. In their work, Balijepally et al. [25] reviewed the usage of cluster analysis in information systems researches published in four information system journals and provided guidelines for future improvement of the application of cluster analysis in information systems researches.

When looking at the usage of cluster analysis in BI research, one of the examples is the work of Fourati-Jamoussi and Niamba [26] who performed a cluster analysis to identify the different profiles of the users of the BI tools, highlighting the importance of user perception in designing BI tools. Also, Raber et al. [27] used cluster analysis in order to construct already mentioned Capability Maturity Model for BI [20].

2.3 Impact of organizational culture to usage of information systems and organizational performance

Organizational culture is the way of life within the organization. According to Schein [28], an organizational culture is "a pattern of basic assumptions invented, discovered, or developed by a given group as it learns to cope with its problems of external adaptation and internal integration, that has worked well enough to be considered valid and, therefore is to be taught to new members as the correct way to perceive, think, and feel in relation to those problems". Another definition, as provided in Economic lexicon [29], defines organizational culture as set of values and behaviors which contribute to the unique social and psychological environment of the organization. Organizational or enterprise culture is based on shared attitudes, beliefs and customs, as well as written and unwritten rules that have evolved over time and are considered valid by all employees within a company. It is mainly invisible, but very powerful social force [30], which can be relevant in various areas, such as e-service research [31].

Existing literature offer a number of different typologies of organizational culture. For the purpose of this research, an organizational culture typology given by Cameron and Quinn [32] has been accepted. It classifies organizational culture into four types, being: (1) clan, (2) adhocracy, (3) market and (4) hierarchy [32].

The role of organizational culture in achieving higher business results and better OP has intrigued researchers for a few decades (e.g. Deal and Kennedy [33], Denison [34], Marcoulides and Heck [35], Barney [36]). In recent period, there are also a number of studies dealing with organizational culture influence on the performance of the organization. Based on extensive correlational analysis, Balthazard et al. [7] argue that constructive organizational culture has a positive impact on OP, while dysfunctional defensive organizational culture has a negative impact on OP. Jacobs et al. [11] examined the associations between organizational culture and performance in healthcare organizations and concluded that organizational culture has a significant role in achieving higher performance. Naranjo-Valencia et al. [12] report clan and adhocracy organizational culture to have a positive impact on OP, while hierarchy and market organizational culture resulted with a negative impact.

3. Methodology

This section presents the methodology used for this research, giving the overview of the research instrument and sample characteristics as well as the presentation of the k-means clustering procedure.

3.1 Research instrument

This study is based on the questionnaire developed by the PROSPER research group. The designed questionnaire is comprised out of 12 parts referring to: (1) BPM maturity, (2) usage of social BPM, (3) BI maturity, (4) CPM, (5) BPM/CPM alignment, (6) BPM/BI alignment, (7) BI/CPM alignment, (8) process performance assessment, (9) OP assessment, (10) organizational culture assessment, (11) company characteristics and (12) demographic respondents' characteristics. For the purpose of this paper, besides the company characteristics, three parts were taken into further analysis: (1) BI maturity, (2) organizational culture assessment, and (3) OP assessment.

3.1.1 Measurement of business intelligence maturity and organizational performance

BI maturity part of the questionnaire has been developed based on the BI maturity model proposed by Dinter [21]. However, for the purpose of this research, Dinter's original model has been reduced to ten questions, providing that all the relevant maturity aspects have been included in the measurement instrument. For each question, two opposite statements (A and B) are provided as answers. Respondents state their level of agreement for each question using the 5-points Likert scale, with 1 representing total agreement with the statement A, while the 5 is representing total agreement with the opposite statement B. The questions refer to: (1) the scope of BI systems use, (2) the level of data architecture maturity, (3) the relevance of BI for the organization, (4) the level of technical architecture maturity, (5) the level of data management maturity, (6) type of BI tools used within the organization, (7) organizational structure related to BI, (8) the level of BI processes maturity, (9) the level of BI profitability assessment and (10) BI strategy.

The constructs for assessing the OP within the organizations are being designed based on the research conducted by Law and Ngai [37]. This section of the questionnaire consists of five statements referring to: (1) level of customer satisfaction with products/services, (2) customer retention rate, (3) sales growth rate, (4) profitability of the organization and, (5) competitive position of the organization. Respondents expressed their level of agreement with each statement on the Likert scale from 1 to 5, where 1 represents total disagreement while 5 represents total agreement. The OP assessment is based on the method of self-evaluation which has been proven in previous researches as a valid method of assessing OP [37].

3.1.2 Measurement of dominant organizational culture

In the designed questionnaire, organizational culture assessment is based on the Organizational Culture Assessment Instrument (OCAI), developed by Cameron and Quinn [32]. It contains six groups of statements referring to: (1) dominant characteristics, (2) organizational leadership, (3) management of employees, (4) organizational glue, (5) strategic emphasis and, (6) criteria for success. Each of these groups of statements contains four statements representing one of the four organizational culture types, as stated earlier. In each group of statements, respondents are supposed to divide total of 100 point among the four proposed statements, based on the similarity with the situation in surveyed company. The dominant organizational culture type is the one with the highest average of collected points. Originally, OCAI assesses both current and preferred organizational culture of the surveyed company. However, for the purpose of this research, only the current organizational culture has been assessed.

3.2 Sample characteristics

This research has been conducted in companies operating in Slovenia and Croatia between March and December of 2016. These two neighbor countries have been selected based on the similar history and characteristics. Moreover, there have already been some researches based on the combined data collected in Slovenia and Croatia (e.g. Škrinjar et al. [38], Buh [39], Hernaus et al. [40]). The sample selection frame for this research has been the Registry of business entities in Croatia and business directory bizi.si in Slovenia where all middle-sized and large companies have been alphabetically sorted and chosen in the random sample by method of steps with the help of random number table. The questionnaires have been distributed in paper forms and as an online survey. Within the companies, the request for participation has been sent to the members of top management or person in charge of BI and BPM. In Slovenia, the questionnaires have been sent to 1394 organizations out of which 171 responses have been received, which makes 12.27% response rate. In Croatia, the questionnaires have been sent to 500 organizations out of which 101 responses have been received, making response rate of 20.2%. Further, before the analysis, the collected data has been checked for missing values and revised for possible outliers and response illogicality.

Final sample consisted of overall 177 responses out of which 109 responses were from Slovenia and 68 responses were from Croatia. When it comes to the size of the respondent’s company in terms of the number of employees, most of them (47.5%) are medium-sized companies, while minority of the companies participating in the study are small companies (10.2%). When looking at the turnover, majority of the surveyed companies had the turnover between 10 and 50 million euros (36.7%), followed by those which had turnover more than 50 million euros (31.6%), while 23.2% of the surveyed companies had turnover lower than 10 million euros. The complete overview of sample characteristics is given by table 1.

When looking at the sample with the regards to the industry sector, following Gelo and Družić [41] we grouped the surveyed companies into five economy sectors. Therefore, in our sample there is a minority of 2.8% of the surveyed companies from the primary sector, while the majority of them are from the secondary sector (35.0%). Table 2 gives the complete overview of the sample structure according to the industry sector.

Table 1. Country of origin and size of the companies in the sample, n=177

Characteristic	Category	Number	Share (%)
Country	Slovenia	109	61.6%
	Croatia	68	38.4%
Number of employees	0-50 employees	18	10.2%
	51-249	84	47.5%
	250-1000	47	26.6%
	1000+ employees	28	15.8%
Turnover	0-10 mill. EUR	41	23.2%
	10 mill. EUR-50 mill. EUR	65	36.7%
	50 mill. EUR+	56	31.6%
	N.A.	15	8.5%

Source: authors' work; Note: N.A. – not available

Table 2. Main industry sector of the companies in the sample, n=177

Characteristic	Category	Number	Share (%)
Industry sector	Primary	5	2.8%
	Secondary	62	35.0%
	Tertiary	53	29.9%
	Quaternary	30	16.9%
	Quinary	20	11.3%
	N.A.	7	4.0%

Source: authors' work; Note: N.A. – not available

3.3 K-means clustering procedure

Cluster analysis provides the means for identification of homogenous groups of observations, cases, units or objects [42]. It assumes that it is possible to find a natural way of grouping that is meaningful to the researcher, although there are no known groups or their number previous to the analysis. The objective of the cluster analysis is to find an optimal way of grouping where observations within each cluster have similar characteristics. Contrariwise, different clusters are mutually different meaning that observations belonging to different clusters have different characteristics.

Cluster analysis begins with selecting the variables for the analysis, followed by the selection of clustering procedure which governs the way clusters are formed. For the purpose of this study, k-means clustering procedure has been selected. According to Hartigan and Wong [43], it is a procedure which divides "*M* points in *N* dimensions into *K* clusters so that the within-cluster sum of squares is minimized". The procedure iteratively observes means of the clusters in a way that observations are simultaneously relocated into the cluster with the closest mean [44]. K-means cluster analysis continues to recalculate clusters' means and relocate observations in as many steps as needed until no observation is relocated into a different cluster.

4. Results

This section presents the results of the study of impact of business intelligence to OP, with the regards to the organizational culture.

4.1 Descriptive analysis

In order to gain a better insight and as a basis for cluster analysis, the descriptive statistical analysis of individual indicators of BI maturity, OP and organizational culture for 177 observed companies from Croatia and Slovenia has been conducted. Moreover, the descriptive statistical analysis of summary indicators of BI maturity, OP and organizational culture has also been conducted. Table 3 presents the explanation of the research instrument indicators.

Table 3. Research instrument indicators

Indicator group	**Indicator code**	**Indicator**
Business intelligence maturity (BI)	BI1	The scope of business intelligence systems usage
	BI2	The level of data architecture maturity
	BI3	The impact of business intelligence
	BI4	The level of technical architecture maturity of BI
	BI5	The level of data management maturity
	BI6	Type of BI tools used within the organization
	BI7	The organizational structure related to BI
	BI8	The level of maturity of BI processes
	BI9	The level of the profitability assessment of BI
	BI10	The level of BI strategy
Organizational performance (OP)	OP1	Value for money
	OP2	Customers retention rate
	OP3	Sales growth rate
	OP4	Profitability of the company
	OP5	Overall competitive position
Organizational culture assessment (OC)	OC1	Dominant characteristics
	OC2	Organizational leadership
	OC3	Management of employees
	OC4	Organization glue
	OC5	Strategic emphases
	OC6	Criteria of success

Source: authors' work

4.1.1 Business intelligence maturity and organizational performance

The analysis of the collected BI maturity and OP data has begun with descriptive statistics of the individual indicators of BI maturity and OP, as shown by table 4. Results reveal that the indicator BI4 indicating the level of technical architecture maturity of BI has the highest mean of 3.67 with the standard deviation of 1.241. On the contrary, the lowest mean is present with the indicator BI9 representing the level of the profitability assessment of BI with the mean of 2.70 and the standard deviation of 1.355, which is also the highest standard deviation among BI maturity indicators. The lowest standard deviation of 1.097 is visible with the BI5 indicator, representing the level of data management maturity. Among OP indicators, the highest mean of 3.93 and at the same time the lowest standard deviation of 0.761 is present with the OP1 indicator, representing the level of customer satisfaction with products/services of the company. On the other hand, the lowest mean of 3.27 with the highest standard deviation of 1.024 among OP indicators is visible at OP4 indicator, representing the profitability of the organization.

Table 4. Descriptive statistics of individual indicators of business intelligence maturity and organizational performance, n=177

Indicator	**N**	**Min**	**Max**	**Mean**	**St. Dev.**
Business intelligence maturity					
BI1	177	1	5	3.21	1.265
BI2	177	1	5	3.38	1.107
BI3	177	1	5	3.50	1.114
BI4	177	1	5	3.67	1.241
BI5	177	1	5	3.62	1.097
BI6	177	1	5	3.28	1.243
BI7	177	1	5	3.20	1.267
BI8	177	1	5	3.12	1.099
BI9	177	1	5	2.70	1.355
BI10	177	1	5	3.02	1.263
Organizational performance indicators					
OP1	177	1	5	3.93	0.761
OP2	177	1	5	3.84	0.845
OP3	177	1	5	3.28	0.993
OP4	177	1	5	3.27	1.024
OP5	177	1	5	3.45	1.005

Source: authors' work

In order to test convergent validity, a factor analysis has been conducted. Table 5 represents the factor loadings of individual indicators of BI maturity and OP. As it is visible from the table 5, all indicators of BI have been classified as factor 1, comprising BI variable. Similar, all indicators of OP have been classified as factor 2, comprising OP variable as OP. In case of BI, indicator BI6 representing the type of BI tools used within the organization has the most powerful influence to BI, while indicator BI9 representing the level of the profitability assessment of BI has the least powerful influence. In case of OP, the most powerful influence is visible with indicator OP5 representing the overall competitive position of the company, while the least powerful influence is present with indicator OP1 representing the level of customer satisfaction with products/services of the company. All of the calculated factor loadings indicate positive influence of indicators to overall variables for both BI and OP.

Figure 1 represents the plot of two-factor rotated solution and the plot of eigenvalues of individual indicators of BI maturity and OP. As it is visible from the figure 1, there are no critical outliers which should be left out of the further analysis. The plot of eigenvalues shows that the most of the variance in data can be accounted for by two eigenvectors. The plot of two-factor rotated solution of factor loadings for BI and OP indicators demonstrates the two independent factors, as it was already shown also by table 5.

Table 5. Factor loadings of individual indicators of business intelligence maturity and organizational performance, n=177

Indicator	**Factor 1**	**Factor 2**
BI1	0.809	
BI2	0.759	
BI3	0.661	
BI4	0.762	
BI5	0.790	
BI6	0.850	
BI7	0.777	
BI8	0.837	
BI9	0.680	
BI10	0.805	
OP1		0.618
OP2		0.775
OP3		0.870
OP4		0.819
OP5		0.875

Source: authors' work

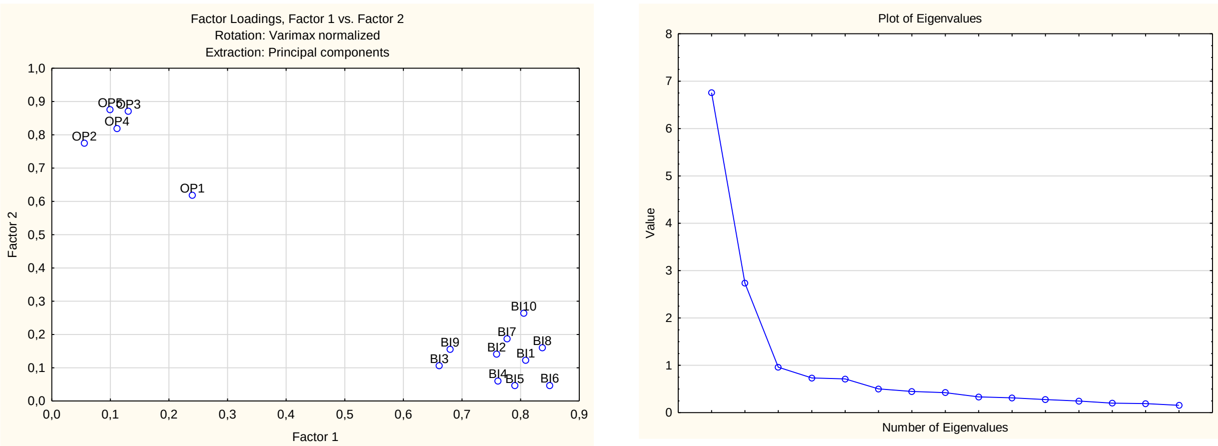

Fig. 1. Factor loadings and plot of eigenvalues of individual indicators of business intelligence maturity and organizational performance

Table 6 presents the descriptive statistics of summary indicators of BI maturity and OP within the observed companies in Croatia and Slovenia. Average level of BI maturity is 3.270 with the standard deviation of 0.945. Average OP grade for the observed companies is 3.551 with the standard deviation of 0.751. In order to test the internal consistency and the reliability of the research instrument, Cronbach's alpha coefficients for BI and OP have been calculated. Both BI and OP summary indicators have Cronbach's alpha coefficients higher than the cut-off value of 0.70 recommended by Nunnally and Bernstein [45]. Therefore, the internal consistency and the reliability of the research instrument have been confirmed.

Table 6. Descriptive statistics of summary indicators of business intelligence maturity and organizational performance, n=177

Indicator	N	Min	Max	Mean	St. Dev.	Cronbach's alpha
BI	177	1	5	3.270	0.945	0.929
OP	177	1	5	3.551	0.751	0.866

Source: authors' work

Table 7 shows the Pearson's correlation matrix for the observed companies summary BI maturity and summary OP variables. It is visible that there is a weak positive correlation between summary BI maturity variable and summary variable for OP. This correlation is statistically significant at the 5% significance level. Based on the presented Pearson's correlation matrix, figure 2 presents the scatter plot of summary indicators of BI maturity and OP.

Table 7. Pearson's correlation matrix, h=2 variables, n=177 companies

Variable	Summary BI	Summary OP
Summary BI	1.000	0.301*
Summary OP		1.000

Source: authors' work; Note: * - statistically significant correlations at the 5% significance level

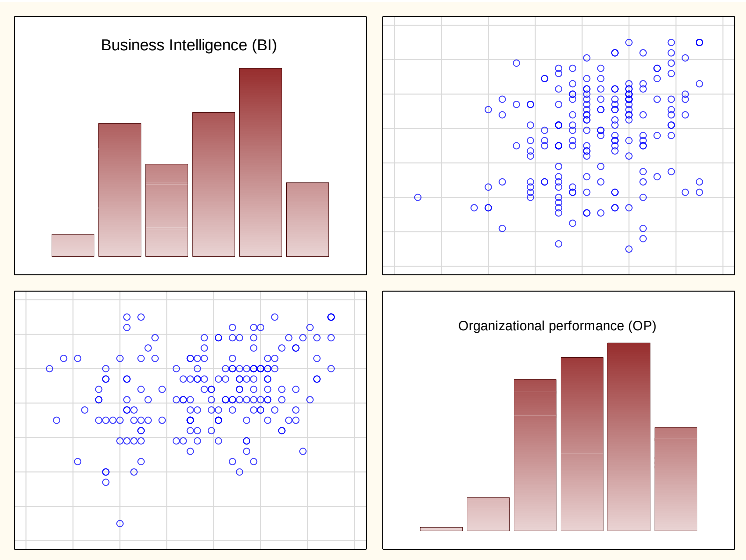

Fig. 2. Scatter plot of summary indicators of business intelligence maturity and organizational performance

4.1.2 Organizational culture of sample companies

The descriptive statistics of indicators of the organizational culture of the observed companies is presented by the table 8. Among the dominant characteristics group of indicators, the highest average of 28.82 with the standard deviation of 18.906 is in the case of the OC1c indicator which represents the strong focus on achieving goals, completing tasks and competitive employees. The lowest average of 23.46 with the standard deviation of 18.611 is present with the OC1a indicator, representing clan culture characteristics to be dominant. Within the organizational leadership group of indicators, the highest average of 33.36 with the standard deviation of 19.634 belongs to the OC2d indicator, representing the coordinated and organized leadership which provides smooth performance. The lowest average of 20.80 with the standard deviation of 13.876 belongs to the OC2b indicator, representing the innovative and entrepreneurial leadership prone to taking risks. In the management of employees group of indicators, the highest average of 32.34 with the standard deviation of 18.798 is visible with the OC3a indicator, representing the teamwork, consensus and cooperation, while the lowest one is present with the OC3b indicator (19.88 with the standard deviation of 14.230), representing the individual risk taking, innovation, freedom and uniqueness. In the fourth group of indicators, dedicated to organizational glue, the highest average of 30.34 with the standard deviation of 18.553 belongs to the OC4a indicator, representing the loyalty and mutual trust and as the core values on which the company is based on. On the contrary, the lowest average of 18.40 with the standard deviation of 12.570 is visible for the OC4b indicator, representing the commitment to innovation and development as well as the focus on setting new guidelines. The strategic emphasize group of indicators revealed the highest average of 31.19 with the standard deviation of 20.646 for the OC5d indicator, representing strong focus on sustainability and stability with the great importance of effectiveness, control and smooth operation of the company. In contrast, the lowest average of 20.40 with the standard deviation of 12.120 is present with the OC5b indicator which represents strong focus on acquiring new resources, setting new challenges, trying out new approaches and finding opportunities. In the last group of indicators, dedicated to criteria of success, the highest average of 36.68 belongs to the OCd6 indicator which represents efficiency based success and importance of reliable delivery, smooth production and low operating costs. The lowest average in this group of indicators belong to the OCb2 indicator (17.97 with the standard deviation of 12.022) which represents success based on the possession of unique and new products and/or services. In that case, a company is a leader in product and/or service innovation.

Table 8. Descriptive statistics of indicators of organizational culture

Indicator	**N**	**Min**	**Max**	**Mean**	**St. Dev.**
		OC1 – Dominant characteristics			
OC1a	177	0	100	23.46	18.611
OC1b	177	0	100	23.53	16.825
OC1c	177	0	100	28.82	18.906
OC1d	177	0	100	24.14	20.814
		OC2 – Organizational leadership			
OC2a	177	0	100	23.82	16.485
OC2b	177	0	100	20.80	13.876
OC2c	177	0	100	21.96	19.470
OC2d	177	0	100	33.36	19.634
		OC3 – Management of employees			
OC3a	177	0	100	32.4e3	18.798
OC3b	177	0	100	19.88	14.230
OC3c	177	0	100	21.44	18.389
OC3d	177	0	100	26.25	20.598
		OC4 – Organizational glue			
OC4a	177	0	100	30.34	18.553
OC4b	177	0	55	18.40	12.570
OC4c	177	0	100	24.97	17.188
OC4d	177	0	100	26.29	20.759

Indicator	N	Min	Max	Mean	St. Dev.
OC5 – Strategic emphases					
OC5a	177	0	100	24.21	16.712
OC5b	177	0	50	20.40	12.120
OC5c	177	0	90	24.20	14.851
OC5d	177	0	100	31.19	20.646
OC6 – Criteria of success					
OC6a	177	0	100	19.73	14.194
OC6b	177	0	70	17.97	12.022
OC6c	177	0	80	25.67	15.231
OC6d	177	0	100	36.68	20.632

Source: authors' work

The descriptive statistics of summary indicators of organizational culture by types is presented by table 9. Overall, the highest average grade has been given to the hierarchy variable, being the average of 29.652 with the standard deviation of 15.843. The lowest average of 20.164 with the standard deviation of 8.701 belongs to the adhocracy variable. The largest range of points is present with the clan variable, while the smallest range of points belongs to adhocracy variable.

Table 9. Descriptive statistics of indicators of organizational culture

Variable	N	Min	Max	Mean	St. Dev.
Clan	177	0.000	96.667	25.665	12.454
Adhocracy	177	0.000	50.000	20.164	8.701
Market	177	0.000	65.000	24.510	11.575
Hierarchy	177	0.000	85.000	29.652	15.843

Source: authors' work

Table 10 presents the sample according to the dominant organizational culture. The overall sample consists of 33.3% of companies with hierarchy as s dominant organizational culture, followed by the 31.6% of the companies having clan as a dominant organizational culture. On the contrary, only 7.9% of the companies revealed to have adhocracy as their dominant organizational culture.

Table 10. Number of sample companies according to dominant culture, n=177

Characteristic	Category	Number	Share (%)
Organizational culture	Clan	56	31.6
	Adhocracy	14	7.9
	Market	48	27.1
	Hierarchy	59	33.3

Source: authors' work

4.2 K-means cluster analysis

In order to organize collected data into meaningful structures, the k-means cluster analysis has been employed using the statistical software Statistica. First, the graph of the cost sequence has been made in order to determinate the best number of clusters. As shown by the figure 3, it has been suggested that the best number of clusters for this study is two. Graph of the cost sequence illustrates the error function for different cluster solutions which is the average distance of observations in samples which are being tested to the assigned cluster centroids [46].

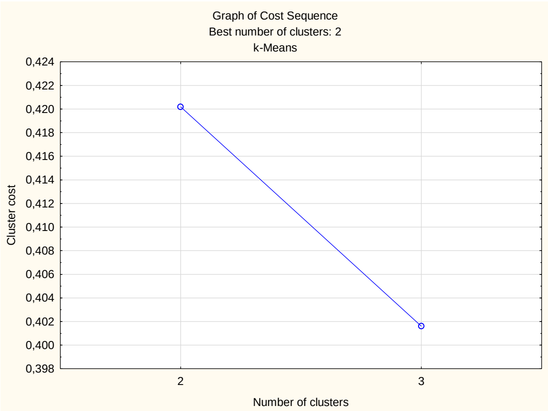

Fig. 3. Graph of the cost sequence

Next, the ANOVA analysis has been conducted for 15 indicators and two clusters on a sample of 177 observed companies. The results of the ANOVA analysis for the BI and OP individual indicators have been presented by the table 11. In the presented case, the null hypothesis which states that the means between observed indicators statistically differ has been rejected with the statistical significance at the 1% level for all observed indicator, except indicator OP2 representing customers' retention rate, where the significance level is at 5%.

Table 11. ANOVA table, k-means clustering, h=15 variables, k=2 clusters, n=177 sample companies

Indicator	**Between sum of squares**	**df**	**Within sum of squares**	**df**	**F-value**	**p-value**
BI1	124.779	1	157.062	175	139.030	0.000**
BI2	68.905	1	146.733	175	82.180	0.000**
BI3	51.586	1	166.662	175	54.167	0.000**
BI4	93.136	1	177.858	175	91.639	0.000**
BI5	69.329	1	142.546	175	85.114	0.000**
BI6	104.696	1	167.180	175	109.593	0.000**
BI7	102.481	1	180.197	175	99.525	0.000**
BI8	95.879	1	116.629	175	143.865	0.000**
BI9	146.851	1	176.279	175	145.785	0.000**
BI10	146.460	1	134.490	175	190.576	0.000**
OP1	7.137	1	94.908	175	13.160	0.000**
OP2	3.567	1	122.004	175	5.117	0.025*
OP3	14.754	1	158.681	175	16.271	0.000**

Indicator	Between sum of squares	df	Within sum of squares	df	F-value	p-value
OP4	9.578	1	174.942	175	9.581	0.002**
OP5	8.998	1	168.743	175	9.331	0.003**

Source: authors' work; Note: * - statistically significant at the 5% significance level; ** 1% level

Table 12 presents the cluster means for the individual indicators of BI and OP. It is visible from the table 12 that 51.98% of the observed companies has been assigned to the cluster 1, while 48.02% of them has been assigned to the cluster 2. Within the cluster 1, the highest mean of 4.370 of the individual indicator is present with the BI4 indicator, representing the level of technical architecture maturity of BI, while the lowest one of 3.489 is visible with the OP4 indicator, representing profitability of the company. Within the second cluster, the highest mean of 3.718 belongs to the OP1 indicator, representing the level of customer satisfaction with products and services of the company, while the lowest mean of 1.753 is present with the BI9 indicator, representing the level of the profitability assessment of BI.

Table 12. Cluster means, k-means clustering, h=15 variables, k=2 clusters, n=177 sample companies

BI & OP individual indicators	Cluster 1	Cluster 2
BI1	4.022	2.341
BI2	3.978	2.729
BI3	4.022	2.941
BI4	4.370	2.918
BI5	4.217	2.965
BI6	4.022	2.482
BI7	3.935	2.412
BI8	3.826	2.353
BI9	3.576	1.753
BI10	3.891	2.071
OP1	4.120	3.718
OP2	3.978	3.694
OP3	3.554	2.976
OP4	3.489	3.024
OP5	3.663	3.212
Number of cases	92	85
Percentage(%)	51.9774	48.0226

Source: authors' work.

Figure 4 presents the distribution of 10 BI individual indicators and 5 OP individual indicators across the two identified clusters. Those distributions give an insight in the amount of differences of the surveyed companies in each cluster according to the observed indicator. The taller the distribution, the differences among the surveyed companies are bigger and vice versa, the narrower the distribution is, the smaller are the differences among the observed companies.

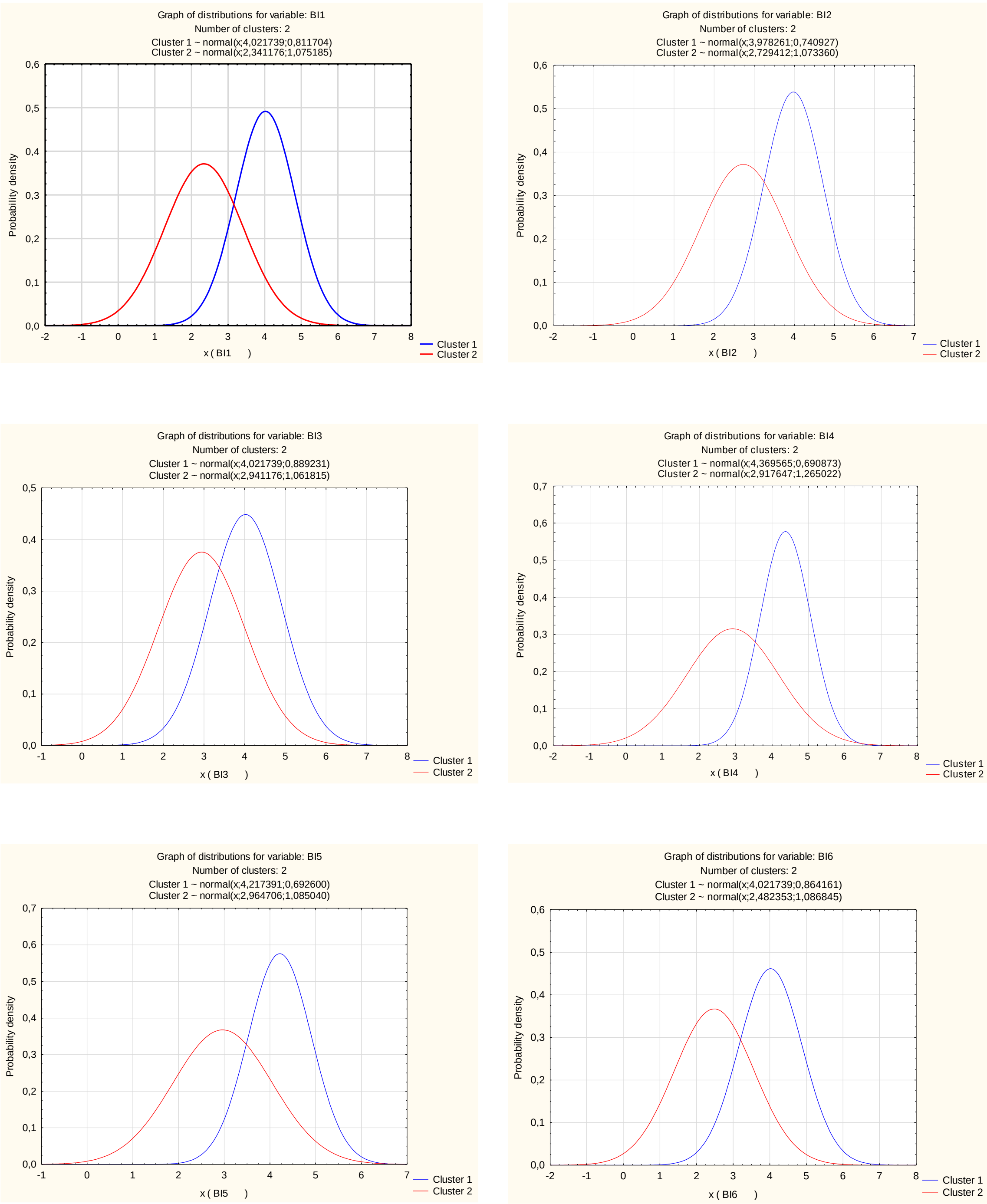

Fig. 4. Distributions of business intelligence and organizational performance indicators across clusters
Note: left curve refers to Cluster 1, and right curve to Cluster 2

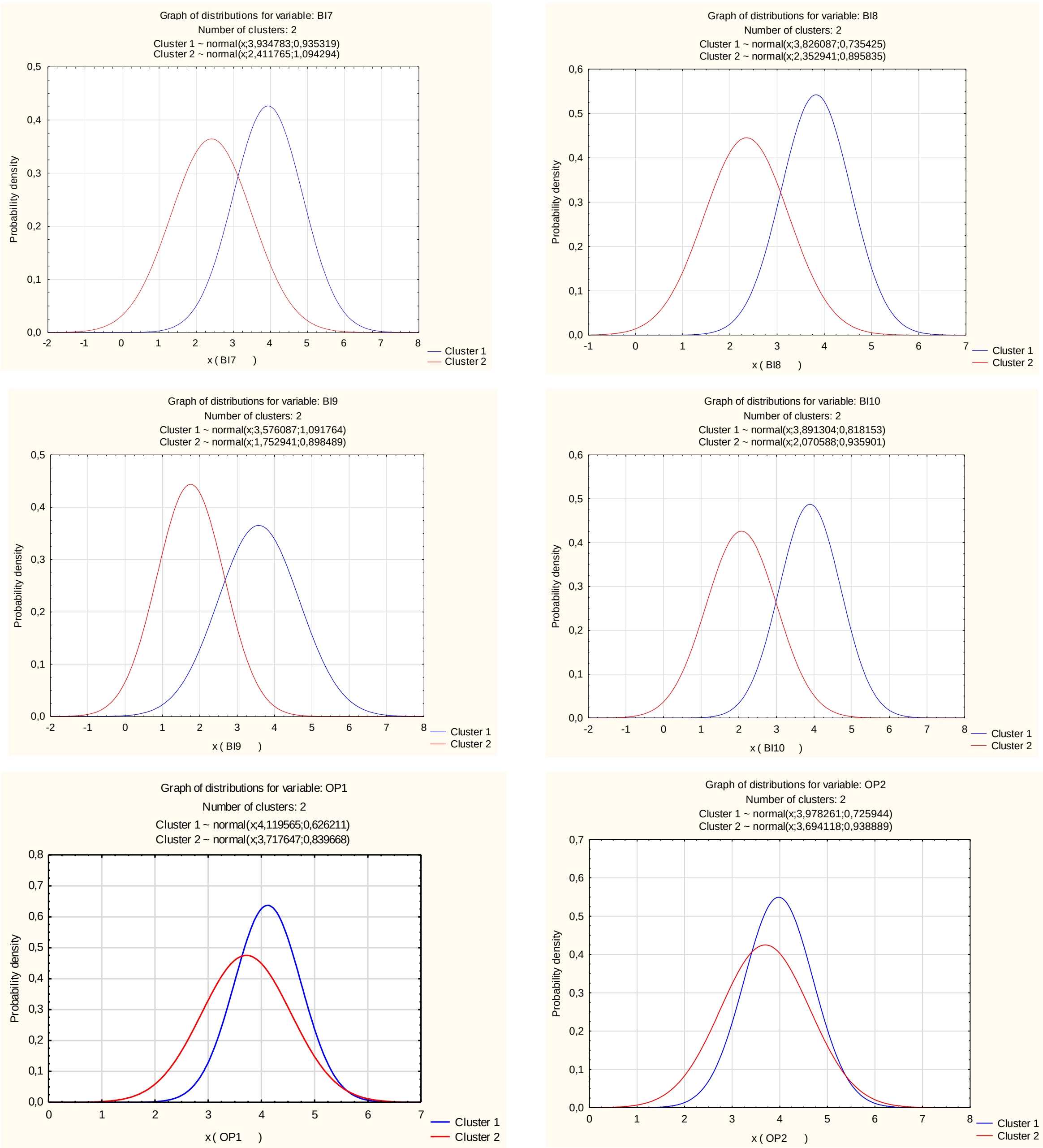

Fig. 4. Distributions of business intelligence and organizational performance indicators across clusters (continued)
Note: left curve refers to Cluster 1, and right curve to Cluster 2

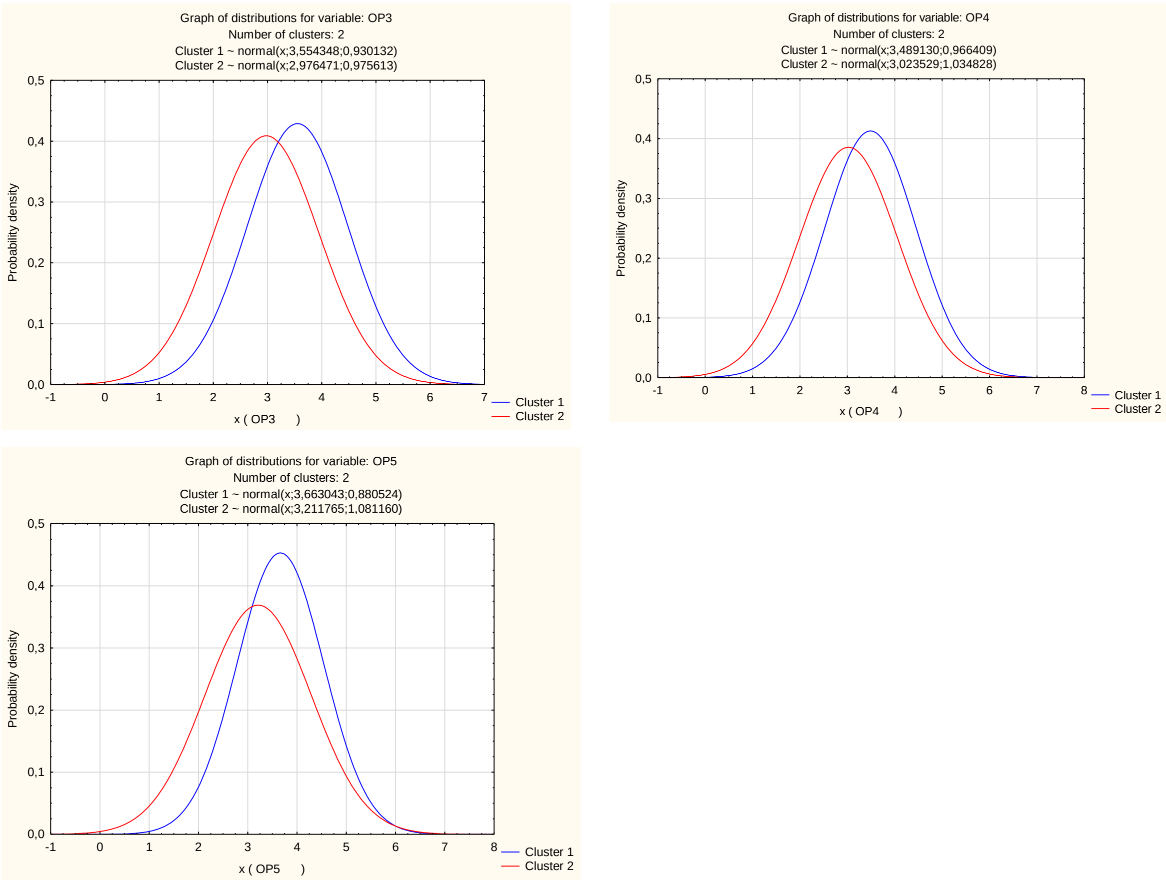

Fig. 4. Distributions of business intelligence and organizational performance indicators across clusters (continued)
Note: left curve refers to Cluster 1, and right curve to Cluster 2

5. Discussion

This section provides a short discussion of the cluster analysis presented in the results section of the paper.

5.1 Characteristics of cluster members according to business intelligence maturity and organizational performance

The k-means analysis of the 177 companies from Croatia and Slovenia identified two clusters. Figure 5 presents the graph of mean values of 10 BI individual indicators and 5 OP individual indicators across two identified clusters. Presented cluster means reveal the existence of differences between clusters according to the observed individual indicators of BI and OP.

Cluster 1 comprises 92 companies. According to the results of the analysis, companies assigned to cluster 1 have higher levels of BI maturity as well as the better OP. The level of technical architecture maturity of BI in those companies is very high which means high level of enterprise-wide data warehouse usage. However, the level of the profitability assessment of BI is low in comparison to other BI indicators. In terms of OP, the highest average among other OP indicators is visible with the level of customer satisfaction with products and services of the surveyed companies. This indicates that the customers of those companies perceive that they receive their money's worth for the products and services of the observed companies. The lowest average results are present with the profitability of the observed companies. However, all of the stated results are still above the average values present in the second cluster.

Cluster 2 consists of remaining 85 surveyed companies. These companies have lower scope of business intelligence systems usage which means that BI is usually used in isolated manner by individuals within the companies in second cluster. Unlike the trend in first cluster, companies from the second cluster have lower level of the usage of dedicated BI storage. On the other hand, similar to trends in cluster 1, companies from cluster 2 also have low average results in profitability assessment of BI which indicates that the companies in this cluster have low or no profitability assessment of BI. When it comes to the OP, the companies from the second cluster have level of customer satisfaction with products and services of the companies as well as the high customers' retention rate. The lowest results are present in case of the sales growth rate which means the sales growth rate is not high above the average of the industry for the observed companies.

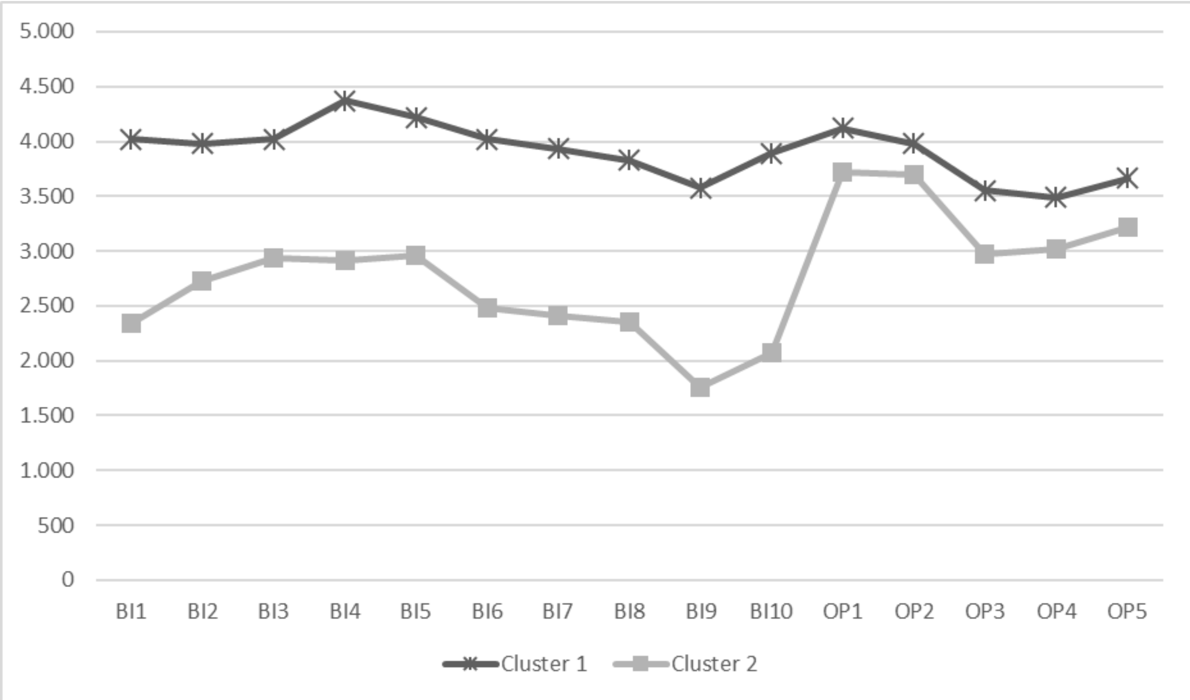

Fig. 5. Graph of the clusters means.

While organizations in both clusters follow very similar pattern in terms of organizational performance (OP1 to OP4), Cluster 1 obviously include mostly the top performers, while in Cluster 2 are mostly the lower performers. Figure 4 and Figure 5 show that the top performers have higher average levels of BI maturity in all its dimensions (BI1 to BI10). Therefore, it is clear that there exists a relationship between BI maturity and organizational performance. While BI mature and BI immature organizations differ significantly in technological aspects, such as the level of technical maturity (BI4) and the types of BI tools used (BI6), the main differences can be found in the organizational dimension, i.e. in the level of profitability assessment (BI9) and the level of BI strategy (BI10), and the scope of usage (BI1). In other words, organizations with higher level of organizational performance use strategic approach to BI implementation with a clearly identified link to the value generated by the use of BI and with this they are also able to provide higher acceptance level of BI. It is reasonable to believe based on these results, that in turn these differences in the approach to BI implementation are reflected in improved organizational performance.

5.2 Differences across clusters according to company characteristics and dominant culture

In order to examine the differences across clusters according to the company characteristics and dominant organizational culture, a cross-tabulation analysis has been conducted. In terms of the country of origin, cluster 1 is comprised of roughly 61% of Slovenian companies and 39% of Croatian companies, while cluster 2 is comprised of roughly 62% of Slovenian companies and 38% of Croatian companies, indicating almost an equal distribution of the companies among clusters with the regards to the country of origin. When it comes to the country of origin and number of employees, there are no statistically significant differences between two identified clusters. However, there are statistically significant differences among the companies of two clusters in terms of the yearly turnover. The results of the cross-tabulation of clusters according to the country of origin and size is presented in table 13.

Table 13. Cross-tabulation of clusters according to country of origin and size

Characteristic	Category	Cluster 1	Cluster 2	Chi-square (p-value)
Country	Slovenia	56	53	0.041
	Croatia	36	32	(0.839)
Number of employees	0-50 employees	8	10	1.302
	51-249	43	41	(0.729)
	250-1000	24	23	
	1000+ employees	17	11	
Turnover	0-10 mill. EUR	18	23	10.002*
	10 mill. EUR – 50 mill. EUR	36	29	(0.019)
	50 mill. EUR+	35	21	
	N.A.	3	12	

Source: authors' work; Note: * - statistically significant at the 5% significance level; N.A. – not available

Table 14 presents the results of the cross-tabulation of clusters according to the industry. There is an equal number of companies from secondary and tertiary sector present in the cluster 1 (both 36%), while the most companies assigned to second cluster (34%) is from the secondary sector and, in comparison to the first cluster, cluster 2 is comprised of a more companies from the quinary sector. However, there is no statistically significant difference between clusters regarding the industry type of the observed companies.

Table 14. Cross-tabulation of clusters according to industry

Characteristic	Category	Cluster 1	Cluster 2	Chi-square (p-value)
Industry	Primary	2	3	10.205
	Secondary	33	29	(0.070)
	Tertiary	33	20	
	Quaternary	17	13	
	Quinary	5	15	
	N.A.	2	5	

Source: authors' work; Note: N.A. – not available

The results of the cross-tabulation of clusters according to the dominant organizational culture is presented in table 15. The dominant organizational culture among the companies from the cluster 1 is the clan culture (38%). According to the Cameron and Quinn [32], the companies with dominant clan culture are family-like, internally focused and flexible, characterized with teamwork, employee involvement programs and corporate commitment to employees. Within the cluster 2, most of the companies (44%) have hierarchy as their dominant organizational culture. Those companies are also internally focused, but at the same time strongly focused on stability and control and characterized by formal procedures, rules and policies [32]. The cross-tabulation analysis revealed statistically significant differences between clusters at the 5% significance level in terms of dominant organizational culture type. These differences could explain the higher average results of the individual BI and OP indicators of the companies from the first cluster in comparison to those from the second one if characteristics of the dominant organizational cultures are taken into consideration. It is important to notice that the use of BI system is mostly voluntary and that it has been shown that socio-organizational factors are the key drivers of BI acceptance and use [47]. Therefore, in organizations with the dominant Clan culture, where the value of BI has been recognized (BI9), the use of BI will be encouraged and will result in high levels of BI usage (BI1). On the other side, in many hierarchical organizations, focused on control and governed by rules and policies, the need to implement and use of BI will not be questioned and therefore the value will not be understood (BI9) to the same extent as in more flexible organizations and its use will not be encouraged (opposed to enforced) throughout the organization (BI1).

Table 15. Cross-tabulation of clusters according to dominant culture

Characteristic	Category	Cluster 1	Cluster 2	Chi-square (p-value)
Organizational culture	Clan	35	21	8.526*
	Adhocracy	9	5	(0.036)
	Market	26	22	
	Hierarchy	22	37	

Source: authors' work; Note: * - statistically significant correlations at the 5% significance level

6. Conclusion

The goal of this paper was to analyze the impact of the level of BI maturity to organizational performance of the company. In that analysis, the role of the organizational culture has been taken into consideration. The paper presented the results of the k-means cluster analysis performed on a sample of 177 companies from Croatia and Slovenia. Overall, two clusters have been identified throughout the analysis. The cross-tabulation analysis of the identified clusters revealed that the dominant organizational culture among the companies assigned to the first cluster is the flexible and friendly clan culture, while the dominant organizational culture among companies from the second cluster is the structured and formal hierarchy culture. Also, the analysis revealed statistically significant differences between clusters in terms of the dominant organizational culture and yearly turnover.

The results of cluster analysis clearly show that **organizations that can be labeled as top performers (Cluster 1) tend to have more mature BI, as opposed to lower performers (Cluster 2)**. While this study is not conclusive in terms of showing causal relationship between BI maturity and organizational performance, it demonstrates importance of all the BI maturity dimensions. Besides, significant differences between in terms of dominant organizational culture type confirm that **some organizational culture settings are more appropriate for achieving higher level of BI maturity**. Considering the nature of different organizational culture types, the most probable explanation of the results is that while the investments in BI technology are important, achieving overall high level of BI maturity go hand in hand and with some organizational culture characteristics which can in turn result in improved organizational performance.

Although this research extends the body of knowledge, there are also some limitations to be recognized. One of the limitations of this research is unequal ratio of responses gathered from Croatia and Slovenia and relatively small number of respondents on which this research is based, so the generalization of conclusions is limited and further validation and research is needed in order to strengthen the conclusions drawn from this paper.

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Biographical notes

Mirjana Pejić Bach, PhD
Mirjana Pejić Bach is a Full Professor at the Department of Informatics at the Faculty of Economics & Business, University of Zagreb. She graduated at the Faculty of Economics & Business Zagreb, where she also received her PhD. degree in Business, submitting a thesis on "System Dynamics Applications in Business Modelling" in 2003. She is the recipient of the Emerald Literati Network Awards for Excellence 2013 for the paper Influence of strategic approach to BPM on financial and non-financial performance published in Baltic Journal of Management. Mirjana was also educated at MIT Sloan School of Management in the field of System Dynamics Modelling, and at OliviaGroup in the field of data mining. She participates in number of EU FP7 projects, and is an Expert for Horizon 2020.

www.shortbio.org/mpejic@efzg.hr

Jurij Jaklič, PhD
Jurij Jaklič is a Professor of Information Management at the Faculty of Economics of the University of Ljubljana. He holds a bachelor degree in applied mathematics from the University of Ljubljana, an MSc in Computer Science from Houston University (USA) and a PhD in Information Management from the Faculty of Economics of the University of Ljubljana. His current main research interests encompass the fields of information quality, business intelligence and business process management. He is the (co)author of around 100 papers and research reports; many of them have been published in international scientific journals such as Decision Support System, Supply Chain Management, Information Research, and Simulation. He has been involved in several research and consulting projects in the areas of business intelligence, business process renovation and IS strategic planning.

www.shortbio.org/jurij.jaklic@ef.uni-lj.si

Dalia Suša Vugec, MA
Dalia Suša Vugec is a Teaching and Research Assistant at the Department of Informatics, Faculty of Economics & Business, University of Zagreb, where she is pursuing her PhD. She graduated with a degree in managerial informatics from the Faculty of Economics and Business in Zagreb, where her master's thesis on unified communications earned the Dean's Award for Excellence. Her main research interests are digital literacy, unified communications, business process management, Web services, Web 2.0 technologies, and e-learning.

www.shortbio.org/dsusa@efzg.hr