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Managerial practices of quality costing: an evidence-based framework

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Abstract

Purpose – This paper aims to use empirical data to classify and contextualize the various practices of quality costing.

Design/methodology/approach – The paper uses 23 "best practices" of quality costing extracted from the literature to survey quality managers of 88 publicly listed Jordanian manufacturing firms. Exploratory factor analysis is then used to create an empirical taxonomic framework.

Findings – Factor analysis of the data identifies a six-factor structure of the practices of quality costing (PQC). Inspection of the component items shows the factors to be conceptually meaningful with none of them containing conflicting items. All factors are reliable and valid and have statistically sound structures.

Research limitations/implications – The classification provided can help managers to better visualize, understand and implement the concept of quality costing. It provides a framework within which practices can be structured and evaluated; managers can identify areas in their firms that are missing and may warrant improvement. The findings should be treated cautiously: the operational definition of PQC derives from an inconsistent literature. Furthermore, the findings are based on self reported data, collected through a questionnaire in Jordan and there is potential source bias or general method variance.

Originality/value – This paper contributes to the body of knowledge through operationalizing the overall concept of quality costing by means of the PQC scale. The six factors identified represent latent constructs within PQC and the component items operationalize such constructs. Furthermore, the procedure provides an illustration of pragmatic application of exploratory factor analysis to empirical managerial data, which can be used in other contexts.

Keywords Quality costs, Managers, Jordan, Quality management, Competitive strategy

Paper type Research paper

1. Background and rationale

Quality is widely acknowledged to be a key competitive weapon in the global marketplace. If it is managed properly, it will not only enhance product differentiation but simultaneously reduce costs. Motivated by the expected benefits from improving quality, many firms around the globe have taken the initiative of obtaining quality labels and certifications. By December 2008 982,832 ISO 9001:2000 certificates had been issued across 176 countries (ISO, 2008). Other firms have gone a step further and embraced the philosophy of TQM. Measuring and reporting quality cost data are a critical step for the successful implementation of quality improvement programs

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(Duncalf and Dale, 1985). To be most beneficial, these programs should be implemented at the lowest possible cost. This, among other things, can be achieved through reducing the costs associated with attaining high quality, which is only possible if such costs are identified, measured and reported (Schiffauerova and Thomson, 2006).

Quality costing has long been promoted as a critical step for the effective planning and implementation of quality improvement programs. The literature reveals some agreement on what is meant by quality costing and its dimensions. However, as yet, there has been no attempt to propose a systematic operational framework of the processes or practices of quality costing.

The purpose of this paper is to draw together the various practices of quality costing by creating an empirically informed theoretical framework against which discretionary managerial practices can be evaluated. It is appropriate to reiterate that the paper is concerned with a taxonomy of costing practices – not of the costs themselves which have already been classified in various ways, such as in the prevention, appraisal and failure model (Feigenbaum, 1974)

2. The "best practices" of quality costing and their classification

Cost of quality reports have been produced for more than 60 years but the literature lacks an agreed definition of quality costing. Previous authors have structured theoretical constructs of what is considered to be "best practice" of quality costing in terms of collecting, measuring, analysing, reporting and using quality cost data (see for example, Morse *et al.*, 1987; British Standards Institute, 1990; Atkinson *et al.*, 1991; Dale and Plunkett, 1991; Tatikonda and Tatikonda, 1996; Bottorff, 1997; Campanella, 1999; Oliver and Qu, 1999; Shah and Mandal, 1999, Prickett and Rapley, 2001; Sower *et al.*, 2007). It is notable that these constructs have not been derived by reference to what actually occurs within "real-life" organisations.

Drawing on the literature's theoretical representation of "best practice", quality costing is defined for the purposes of this paper as the selection, collection, measurement, classification, analysis, reporting and use of the quality cost data. Hence, the practices of quality costing refer to the practices, policies and procedures which relate to the selection, collection, measurement, classification, analysis, reporting and use of the quality cost data. A list of 30 "best practices" of quality costing (PQC scale) was extracted from the literature. These practices were classified, *a priori*, into three groups or subscales:

(1) The first group includes those practices that relate to collecting, measuring, and classifying quality cost data (CMC scale).

(2) The practices in the second group relate to analyzing, reporting, and using quality cost data (ARU scale).

(3) The third group includes the practices referring to selecting, using, and maintaining of quality-related financial metrics (SUM scale).

To improve the generic PQC scale in terms of both content and construct validity it was evaluated by a panel of academic experts, quality consultants and professionals as to the coverage, understandability and clarity of the questions[1]. Furthermore, the scale was pre-tested by quality managers from four different manufacturing firms that had not been included in the sample. The managers were asked to comment on the content of the questions, their coverage, clarity and layout. Based on the feedback received, the PQC scale was refined. A total of seven items were omitted from the scale as they were unclear to the respondents or overlapped with other items. Moreover, wording and layout were modified. The final PQC scale was composed of 23 items as shown in Table I.

3. Method and data

A survey questionnaire[2] was sent to all 88 Jordanian manufacturing firms (JMF) publicly listed at Amman Stock Exchange in December 2007. These firms were requested to have the questionnaire completed by their quality manager or the individual in charge of the quality function, regardless of his title. Companies were asked to indicate

	Item
Collecting, measuring and classifying data	
CMC1	Strategies and methods for measuring and collecting quality cost data are clearly defined
CMC2	Quality costs data are measured and collected on a continuous basis
CMC3	The accounting staff participates in determining which quality cost items are collected
CMC4	The quality cost items collected are categorized under the Prevention, Appraisal, and Failure (PAF) scheme
CMC5	In our firm, for quality costs, we collect and measure only the cost of inspection and internal failure
CMC6	There is a high level of cooperation across departments in the collection and measurement of quality cost data
CMC7	The accounting staff coordinates the process of collecting and measuring quality cost data
Analysing, reporting and using data	
ARU1	Quality costs reports are prepared on a continuous basis
ARU2	Graphs and charts are used to present quality cost data
ARU3	Quality costs data are analyzed across more than one dimension (e.g. process/product line/department)
ARU4	Quality costs data are analyzed into finer levels of cost components
ARU5	Quality costs reports are benchmarked against previous periods, budgeted data and/or against competitors
ARU6	Quality costs reports are made available to senior managers only
ARU7	In our firm, quality costs reports are influential in identifying potential quality problems and improvement opportunities
ARU8	In our firm, quality costs reports are influential in planning and monitoring quality improvement programmes
ARU9	The accounting staff coordinates the process of preparing quality costs reports.
Selecting and using metrics	
SUM1	In our firm, financial quality metrics are used in addition to operational metrics
SUM2	Financial quality metrics in place are directly linked to the objectives of the firm's quality improvement effort
SUM3	The accounting staff is influential in selecting financial quality metrics
SUM4	In our firm, financial quality metrics in place are regularly reviewed
SUM5	In our firm, ratio-based financial metrics are used in addition to absolute values
SUM6	In our firm, financial quality metrics in place cover all functional areas
SUM7	In our firm, the only use of financial quality metrics is to attract top management attention to quality problems and obtain resources

Table I.
The three *a priori* groupings and their multiple items

the extent to which they agree with 23 statements, based on the quality costing related to the management control systems actually in place in their firms, using a five-point scale in which 1 represents disagree strongly, and 5 indicates strong agreement.

A total of 65 usable questionnaires were collected back. The Mann-Whitney U test was used to assess non-response bias between respondents and non-respondents with respect to the firms' characteristics such as total assets, sales turnover, number of employees, age, and ISO 9001 accreditation status. The results showed that non-response bias was not a problem in the current study. The normality test suggested that the distribution of the responses for the PQC scale and each of the subscales is approximately normal, with the significance levels of the Kolmogorov-Smirnov statistics ranging between 0.061 and 0.099.

The reliability coefficient (Cronbach's alpha) for the comprehensive PQC scale was 0.851 which is considerably above the acceptable level of 0.6 (Sekran, 1992). The item-total correlation statistic for all but one of the multiple line items is greater than the minimum acceptable level of 0.3 (Kline, 1986); Item CMC1 had an item-total correlation value of 0.152, below the acceptable level of 0.3. This suggests that this item is incorrectly included in the PQC scale. If it is dropped then the Cronbach alpha coefficient for the PQC scale improves from 0.851 to 0.879. Nevertheless, the final decision to whether drop this item or not was deferred until the factor analysis was performed.

4. Data analysis

4.1 The profile of responding firms

As shown in Table II, the 65 responding firms belonged to 14 different industrial sectors. The total assets of these firms ranged from US$3.5 million to US$592 million with an average of US$68 million. The average number of employees was 370. In 2007, the sales turnover generated by these firms ranged between US$35,000 and US$1.12 million. About 83 per cent of these firms had been operating in the market for more than ten years. Of the 65 firms that responded, 54 per cent were ISO 9001 certified.

4.2 Factor analysis

To better identify the critical dimensions for the practices of quality costing, exploratory factor analysis and reliability analysis were used (Meyers *et al.*, 2006). Factor analysis[3] is not a clear-cut technique but involves judgmental decisions that affect the final solution. For example, decisions have to be made as regard to the factorability of data, extraction method, extraction criteria and so on. These issues are detailed in the Appendix.

4.2.1 Factor analysis on the 23 items of the PQC scale (first run). The 23 items of the PQC scale were subjected to an exploratory factor analysis using the principal component method with Orthogonal rotation[4]. The factorability of the data were assessed. The value of the overall KMO[5] was normal at 0.628 and exceeded the minimum acceptable level of 0.5. Furthermore, the Bartlett's test of sphericity was significant ($\chi 2(253) = 540.732, \rho = 0.000$). The KMO statistics for the all but one individual items ranged from 0.522 to 0.811; Item CMC1 had a KMO statistic of 0.407, which is far below the minimal acceptable level of 0.5.

The initial solution showed that communalities ranged from 0.570 to 0.877. Furthermore, seven factors with eigenvalues greater than or equal to 1 were extracted. These factors accounted for 69.7 per cent of the total cumulative variance with Factor I

Categories	Number
Industrial sectors	
Food, beverage and tobacco	14
Chemical products	7
Pharmaceutical	7
Metal fabricated metal manufacturing	7
Bricks, pottery, glass and cement	5
Paper printing publishing	4
Non-metallic mineral products	4
Electrical appliance component manufacturing	4
Textile, apparel and footwear	3
Mining quarrying	3
Leather and fur goods	3
Coal petroleum products	2
Wood furniture products	1
Machinery equip	1
Total	65
Total assets (US$)	
Small (<7,000,000)	13
Medium (7,000,000-40,000,000)	36
Large (>40,000,000)	16
Number of employees	
Small (<50)	4
Medium (50-499)	53
Large (500 and more)	8
Sales turnover (US$)	
Small (<10,000,000)	40
Medium (10,000,000-60,000,000)	19
Large (>60,000,000)	6

Table II.
Profile of responding firms

being the dominant and explaining 27.6 per cent of the variance. However, the inspection of the scree plot revealed a break in the curve at the fifth factor.

To assist in the interpretation of the retained factors, a Varimax rotation[6] was performed. The rotated solution is shown in Table III. Inspection of the rotated matrix revealed that all factors except Factor VII had a number of good loadings with three or more items loaded on each factor. Only one item loaded on Factor VII; unsurprisingly, this item was CMC1. Almost 25 per cent of the items were cross-loaded.

At this point it was clear that Item CMC1 is a problematic item. Therefore, a decision was made to drop this item and re-perform the factor analysis on the remaining 22 items.

4.2.2 Factor analysis for the remaining 22 items. The remaining 22 items of the PQC scale were subjected to an exploratory factor analysis using the principal component method with Orthogonal/Varimax procedure. The overall KMO increases from 0.628 to 0.684 and the Bartlett's chi square is significant ($\chi 2(231) = 517.5$, $\rho = 0.000$). Both tests indicate that the data are suitable for factor analysis. Furthermore, the KMO for the individual items range from 0.512 to 0.836; communalities range from 0.560 to 0.875. Six factors with eigenvalues greater than or equal to 1 are extracted. These

Table III. Factor analysis-rotated component matrix (first run)

	Component 1	2	3	4	5	6	7
SUM1	0.825	0.199	−0.039	−0.046	0.104	−0.047	0.113
ARU7	0.663	0.038	−0.021	0.092	0.212	0.235	0.142
ARU9	0.566	0.224	0.182	−0.110	0.394	−0.074	−0.040
ARU4	0.564	0.299	0.193	0.100	0.255	0.283	−0.002
ARU8	0.556	−0.084	0.178	0.321	−0.061	0.467	−0.263
SUM7	0.526	−0.028	0.274	0.344	0.082	0.293	0.308
SUM5	0.036	0.914	−0.016	0.083	0.100	0.142	0.051
SUM4	0.229	0.682	0.226	0.120	−0.103	−0.030	−0.166
SUM2	0.440	0.607	0.122	0.352	−0.139	−0.098	0.017
ARU1	−0.034	0.501	0.293	−0.199	0.032	0.460	0.219
CMC5	−0.055	0.129	0.783	0.137	0.239	−0.061	−0.138
CMC6	0.266	−0.001	0.723	−0.027	0.122	0.237	0.146
CMC4	0.060	0.203	0.721	0.127	−0.238	−0.024	0.171
ARU3	0.014	0.143	0.176	0.820	0.018	−0.042	0.129
ARU2	0.100	0.067	0.056	0.771	0.273	0.280	−0.078
ARU6	0.105	0.263	−0.209	0.454	0.430	0.274	−0.002
CMC3	−0.007	−0.029	0.198	0.217	0.747	0.096	0.122
SUM3	0.233	0.043	−0.171	−0.058	0.674	0.031	−0.062
CMC7	0.462	−0.171	0.179	0.302	0.602	0.087	−0.038
ARU5	0.043	−0.048	−0.053	0.116	0.077	0.784	−0.003
CMC2	0.219	0.257	0.093	0.037	0.211	0.630	0.209
SUM6	0.432	0.157	0.299	0.257	−0.169	0.434	0.030
CMC1	0.132	−0.030	0.057	0.065	0.006	0.040	0.912
Eigenvalue	3.27	2.52	2.33	2.18	2.17	2.13	1.44
Variance explained %	14.23	10.95	10.11	9.46	9.43	9.25	6.27

Notes: Extraction method: Principal component analysis, Rotation method: Varimax with Kaiser normalization

factors account for 67 per cent of the total cumulative variance with the first two factors being the dominant ones explaining 29 and 11 per cent of the variance respectively. The scree plot in Figure 1 shows a clear break in the curve after the sixth factor supporting the result of the Kaiser's criterion to retain six factors only.

The rotated matrix (see Table IV) shows that all factors have a number of good loadings and none of them are loaded on less than three items. The highest loading is 0.828 (in Factor II) explaining 68.5 per cent of the item variance, whereas the lowest loading is 0.500 (in Factor V) explaining 25 per cent of the variance. Moreover, the number of cross-loaded items decreases from six on the *a priori* classification to just two (CMC7 and ARU4).

4.2.3 Validating the extracted factors. The Cronbach's alpha coefficient is computed for each derived factor to assess its reliability. The alpha coefficients range from 0.677 to 0.768 (see Table IV). The item-total correlation statistics for the multiple line items are between 0.366 and 0.682. Moreover, the reliability tables produced by SPSS show that for each derived factor, removing any of its items will not improve its reliability. Accordingly, these six factors are judged to be reliable.

The recommendations of Nunnally and Bernstein (1994) were adopted in this study to evaluate the construct validity of the factors. Each of the six factors was subjected to

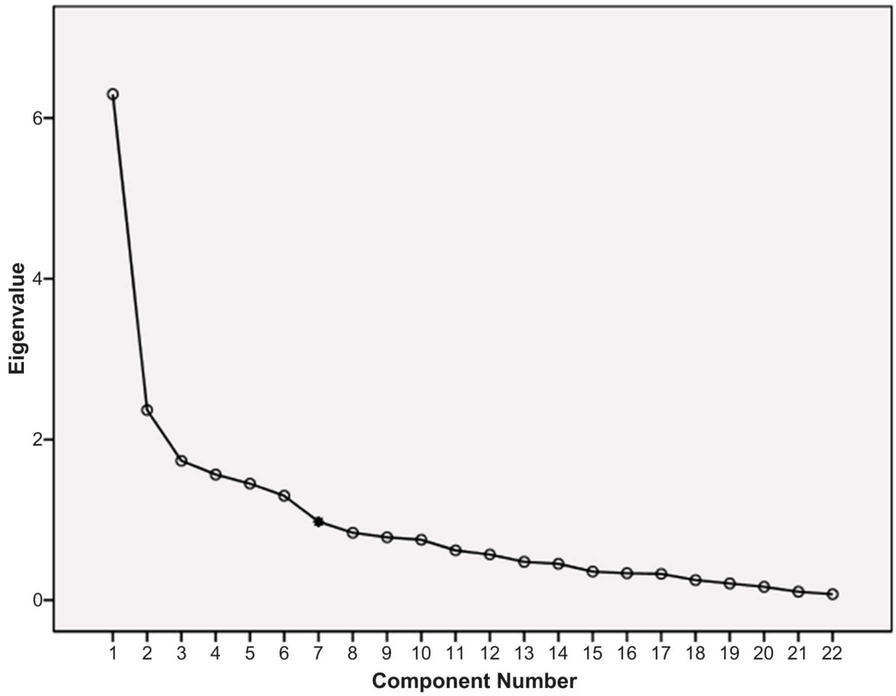

Figure 1.
Scree plot – factor analysis of 22 items

a factor analysis using the principal component method, which results in unifactorial solutions. Accordingly, it can be said that each of the six factors is a valid construct. Furthermore, the KMO values for each factor and for their multiple items are above the minimum acceptable level of 0.5. In addition, the Bartlett's chi square is significant for all six factors.

5. Findings and discussion

The factor solution suggests that there are six distinct components of the PQC listing. These factors represent latent constructs within PQC; items loading on a specific factor are, in effect, operationalizing such latent constructs. However, the fact that a number of items cluster together does not necessarily mean that they jointly create a valid conceptual meaning. Therefore it is necessary to conduct a conceptual inspection of the factors and their items after the factor structure has been determined. Once the conceptual meaning for each factor is substantiated, extracted factors need to be labelled according to the common theme presented by the items loaded on the factor as well as the loading statistic (Mahoney *et al.*, 1995). The inspection and labelling of the factors extracted in the current study are discussed next.

Factor I is a construct (scale) comprising four[7] items namely: SUM7, SUM1, ARU7 and ARU8. As can be seen from Table V, conceptually these items tackle the different uses of the quality cost data and reports. Therefore, it was decided to describe or label this factor as: use of quality cost data (UQCD). This is the dominant factor explaining 14.53 per cent of the total variance with an eigenvalue of 3.20. However, it should be

Table IV. Factor analysis – rotated component matrix (second run)

Item	Component 1	2	3	4	5	6	Cronbach alpha
SUM7	0.726	−0.016	0.020	0.079	0.201	0.132	0.768
SUM1	0.661	0.256	0.244	−0.062	−0.196	−0.069	
ARU7	0.630	0.107	0.255	−0.044	0.021	0.154	
ARU8	0.629	0.036	0.153	0.278	0.248	0.222	
SUM5	−0.094	0.828	0.104	−0.020	0.113	0.257	0.746
SUM4	0.135	0.736	−0.033	0.275	0.087	0.029	
SUM2	0.248	0.734	−0.017	0.099	0.229	−0.061	
SUM6	0.194	0.590	−0.111	0.234	0.213	0.275	
SUM3	0.131	0.039	0.745	−0.172	0.008	0.042	0.687
CMC3	−0.078	−0.119	0.669	0.249	0.192	0.190	
CMC7	0.402	−0.115	0.658	0.175	0.311	−0.037	
ARU9	0.255	0.213	0.551	0.156	−0.143	−0.060	
CMC5	−0.061	0.122	0.185	0.775	0.175	−0.032	0.742
CMC4	0.143	0.242	−0.240	0.725	0.040	0.045	
CMC6	0.241	−0.001	0.143	0.702	−0.039	0.219	
ARU2	0.225	0.059	0.196	0.046	0.813	0.128	0.677
ARU3	0.112	0.203	−0.047	0.211	0.758	−0.075	
ARU5	0.092	0.199	0.285	−0.205	0.529	0.271	
ARU4	0.077	0.406	0.266	0.152	0.500	0.281	
ARU1	0.017	0.233	−0.014	0.306	−0.155	0.714	0.759
CMC2	0.302	0.209	0.194	0.077	0.093	0.712	
ARU6	0.283	−0.206	−0.003	−0.107	0.238	0.636	
Eigenvalue	3.20	2.60	2.51	2.22	2.17	2.02	
Variance explained %	14.53	11.81	11.39	10.09	9.86	9.20	

Notes: Extraction method: Principal Component analysis, Rotation method: Varimax with Kaiser normalization

noted that the percentage of total variance explained by Factor I is not attributed to these four items only; the remaining 18 items of the PQC scale contributed to this percentage too.

Factor II is a construct (scale) comprising four[8] items namely: SUM5, SUM4, SUM2 and SUM6 (see Table V). Conceptually, these items focus on the practices related to selecting and reviewing the financial quality-related metrics. Therefore, the factor was labelled as: Selection of financial quality-related metrics (SFQM). All items in the factor originally come from the *a priori* SUM group. Item SUM5 ("Ratio-based financial metrics are used in addition to absolute values") has the highest loading (0.828) among all groups. Items SUM4 and SUM2 have almost the same loadings, 0.736 and 0.734.

Factor III is a construct comprising four items namely: SUM3, CMC3, CMC7 and ARU9. These items tackle the role played by accounting staff in the process of collecting and reporting the quality cost data and accordingly the factor was labelled as: Role of accounting staff in quality costing (RACC). Item CMC7 can be described as a cross loaded item with loadings of 0.402 and 0.658 on Factors I and III respectively. It was decided to assign this item to Factor III. Statistically, it loads higher on this factor than on Factor I, and conceptually it fits better (is more consistent) with the nature of Factor III than with Factor I.

Factor	Items	Label
Factor I		Use of quality cost data (UQCD)
SUM7	In our firm, the only use of financial quality metrics is to attract top management attention to quality problems and obtain resources	
SUM1	In our firm, financial quality-related metrics are used in addition to operational metrics	
ARU7	In our firm, quality costs reports are influential in identifying potential quality problems and improvement opportunities	
ARU8	In our firm, quality costs reports are influential in planning and monitoring quality improvement programmes	
Factor II		Selection of financial quality-related metrics (SFQM)
SUM5	In our firm, ratio-based financial metrics are used in addition to absolute values	
SUM4	In our firm, financial quality metrics in place are regularly reviewed	
SUM2	Financial quality metrics in place are directly linked to the objectives of the firm's quality improvement effort	
SUM6	In our firm, financial quality metrics in place cover all functional areas	
Factor III		Role of accounting staff in quality costing (RACC)
SUM3	The accounting staff is influential in selecting financial quality metrics	
CMC3	The accounting staff participates in determining which quality cost items are collected	
CMC7	The accounting staff coordinates the process of collecting and measuring quality cost data	
ARU9	The accounting staff coordinates the process of preparing quality costs reports	
Factor IV		Collection and classification of quality cost items (CCQI)
CMC5	In our firm, for quality costs, we collect and measure only the cost of inspection and internal failure	
CMC4	The quality cost items collected are categorized under the prevention, appraisal, and failure (PAF) scheme	
CMC6	There is a high level of cooperation across departments in the collection and measurement of quality cost data	
Factor V		Sophistication of analysis and presentation of quality cost data (SOAP)
ARU2	Graphs and charts are used to present quality cost data	
ARU3	Quality costs data are analyzed across more than one dimension (e.g. process/ product line/ department)	

(*continued*)

Table V.
The empirical factors with their multiple items and suggested labels

Table V.

Factor	Items	Label
ARU5	Quality costs reports are benchmarked against competitors or against previous periods	
ARU4	Quality costs data are analyzed into finer levels of cost components	
Factor VI		Frequency of collection and reporting quality cost data (FOCR)
ARU1	Quality costs reports are prepared on a continuous basis	
CMC2	Quality costs data are measured and collected on a continuous basis	
ARU6	Quality costs reports are made available to senior managers only	

Factor IV represents a construct comprising three items namely: CMC5, CMC4 and CMC6. It has been labelled as: Collection and classification of quality cost items (CCQI). The common theme for CMC5 and CMC4 is the type of quality costs elements collected. On the other hand, item CMC6 focuses on the level of cooperation across departments in collecting and measuring quality costs items. At first glance the first two items appear to be unrelated to (inconsistent with) the third item. However, deeper consideration explains this relationship. Before collecting quality cost data, the firm has to define its cost categories (classification) and identify, within each category, the types of payments to be coded as quality costs. Some quality cost elements are easy to identify and collect as they are direct and come from one department (Rust, 1995). For example, appraisal costs arise in the quality assurance department, and internal failure cost like scrap, rework, and spoilage cost come from the operation department (Dale and Plunkett, 1991). However, these cost elements represent a small portion of the total quality costs and are already captured by the existing accounting system. On the other hand, the majority of quality costs are indirect and often fall across departmental boundaries. These cost elements are neither captured effectively nor reported through the traditional accounting system. Without the cooperation and support of the related departments, it is difficult to identify these elements and hence to collect and measure them. In the absence of intelligent leadership and inter-departmental cooperation this can lead firms to simply report the traditional appraisal and internal failure cost elements already produced by the existing system (Atkinson *et al.*, 1991). Therefore, the higher the cooperation and support of other departments, the more types of quality costs elements are collected.

Factor V includes four items namely: ARU2, ARU3, ARU5 and ARU4. Conceptually, these items focus on the way quality cost data are analyzed, benchmarked and presented in the report. Therefore, the factor was labelled as: Sophistication of analysis and presentation of quality cost data (SOAP). All items in the factor are originally from the ARU *a priori* group. Item ARU4 has loadings of 0.500 and 0.406 on Factor V and Factor II respectively. According to the criteria used in the current study this item belongs to Factor V since it displays a higher statistical loading on that factor. Furthermore, from a conceptual point of view it is more consistent with the common theme of Factor V.

Factor VI had the lowest explanatory power of 9.20 per cent and has been given the label of: Frequency of the collection and reporting of quality cost data (FOCR). It includes three items: CMC2, ARU1 and ARU6. Items CMC2 and ARU1 focus on the timing of collecting and reporting quality cost data. Item ARU6 is concerned with whether or not quality costs reports are circulated to all managers. The focus of the three items appears to be inconsistent but careful examination shows that they are related. The argument is based on recognition that top management is responsible for allocating the resources for the different activities and projects in the firm. Furthermore, top management speaks in the language of money. Therefore, quality improvement teams use the quality cost data and reports, mainly to describe for management the cost and benefit of proposed improvement with an aim of obtaining the required resources. In such situation, the quality costs report needs to be circulated to top management only. Therefore, it is expected that where quality cost data are collected and reported on a continuous basis, it is unlikely to be circulated across the whole firm. Looked at the other way round, if quality cost data are collected only periodically then they are more likely to be widely disseminated.

6. Conclusion, implications and limitations

As discussed earlier, the literature lacks an agreed definition of what is meant by quality costing and its dimensions. What the literature does provide is a number of "best practices" in terms of identifying, collecting, measuring, analysing, reporting and using quality cost data. Bringing these references together has allowed us to develop of an authoritative list of discretionary managerial practices of quality costing. This PQC scale is in effect an operational definition of quality costing. The items of this scale were classified into three *a priori* groups, namely: CMC, ARU and SUM. However, the exploratory factor analysis performed on the PQC items produces a more sophisticated model with six empirical groupings as shown in Table V and Figure 2. Three of the empirical groups can be described as heterogeneous since their items come from two or more *a priori* groups. The inspection of the empirical groups and their items shows them to be conceptually meaningful. None of them contains contrasting items and all of them have a statistically sound structure.

The findings of the exploratory factor analysis have important implications in relation for the literature and managers. They contribute to the quality costing literature through operationalizing the overall concept of quality costing by means of the PQC scale. Furthermore, the classification of the practices of quality costing that we have established can help managers to better visualise, understand and implement the concept of quality costing. In addition, it can be used as framework against which individual firms' management control systems can be evaluated. By carrying out a self-assessment exercise of the practices in their firms, managers can identify areas that may warrant improvement. Finally, the procedure described provides an illustration of pragmatic application of exploratory factor analysis to empirical managerial data, which can be used in other contexts.

However, the findings need to be treated with caution. The operational definition of PQC, in the current study, is based on the "best practices" detailed in an inconsistent literature which lacks precise definition, conceptual or operational, of quality costing. Furthermore, the findings are based on self-reported data, collected through a questionnaire in Jordan and thus there is a possibility of source bias or general method variance.

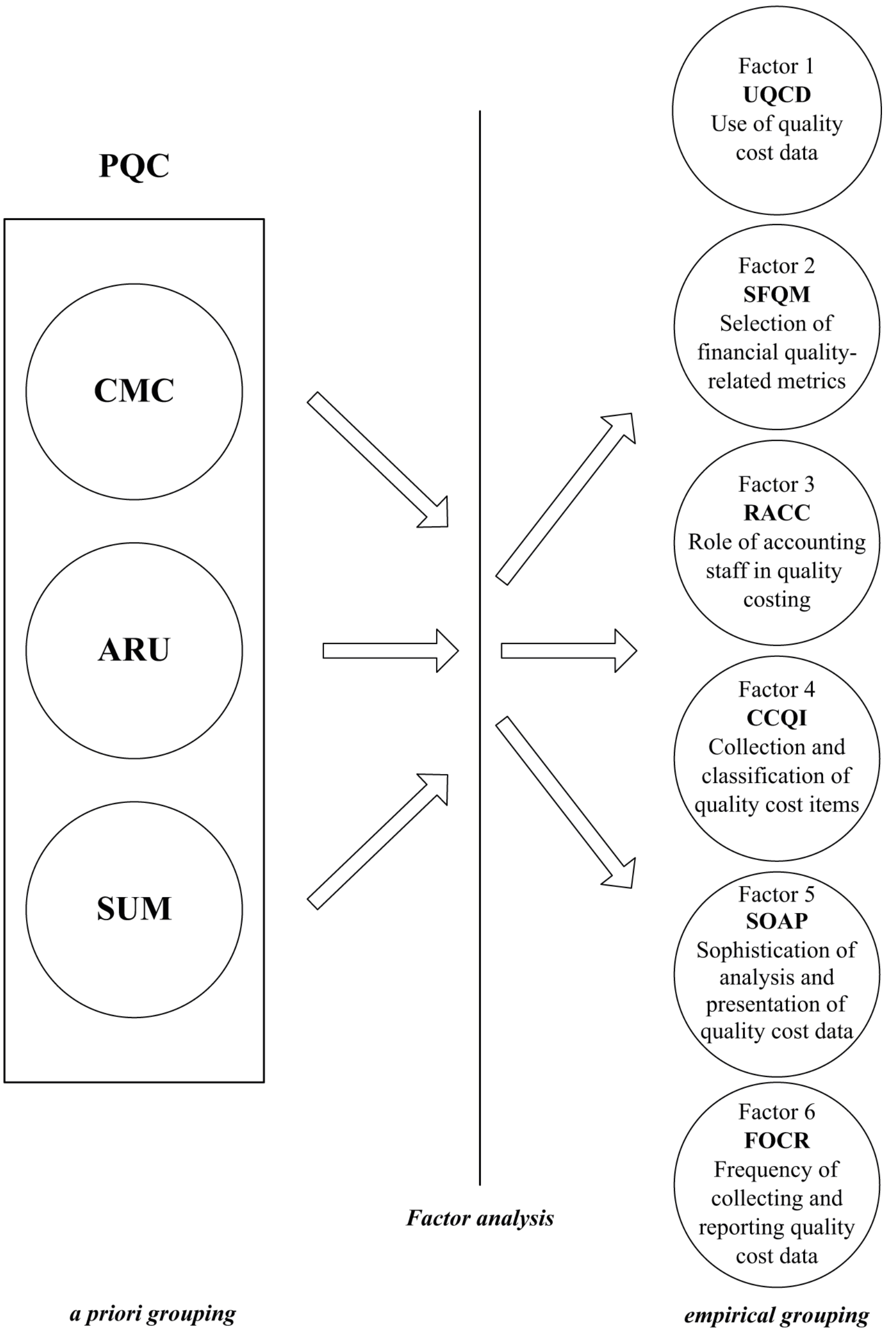

Figure 2.
A priori grouping versus empirical grouping for the PQC items

Notes

1. As recommended by Nunnally and Bernstein (1994).
2. A copy of the questionnaire can be provided on request.
3. Factor analysis is a statistical technique that examines the relationships among a wide range of data sets to uncover the underlying dimensions (factors) among them (Kim and Mueller, 1978). This permits a large number of observed variables to be summarized into a fewer number of factors with a minimum loss of information. Thus, factor analysis could be used to verify the conceptualization of a construct of interest (Hair *et al.*, 1992).
4. The orthogonal rotation method assumes that the factors are not related. To check this assumption the 23 items of the PQC scale were subjected to an exploratory factor analysis using the oblique rotation method. The correlation coefficients among the extracted factors were examined. All these coefficients were below 0.22. Therefore it is reasonable to assume that the factors are not related. In this case, both, the oblique and orthogonal rotations yield similar solutions (Field, 2005).
5. Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) is a test used to assess the suitability of the data set for factor analysis (Field, 2005). It compares the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. It is calculated for both individual and multiple variables. The value of the KMO statistic ranges from 0 to 1. The higher the value of the KMO statistic, the more suitable is factor analysis for the given data set. According to Kinnear and Gray (2000) a KMO value ≥ 0.5 means that it is appropriate to proceed with the factor analysis for the given data set.
6. Varimax (variance maximizing) is an orthogonal type of rotation that attempts to maximize the variance of loadings within factors. As a result, a small number of variables are highly loaded onto each factor. This clarifies the true contents of each factor and makes interpretation much easier (see Tabachnick and Fidell, 2006).
7. According to the cut-off point (0.4) adopted in the current study, item CMC7 has a loading of 0.402 on Factor I. However, this item is ascribed to Factor III. This issue is addressed when Factor III is discussed.
8. Item ARU4 has loadings above the 0.4 cut off point on both Factor II and Factor V. This issue is addressed when Factor V is discussed.

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Appendix. Choice of appropriate factor analysis techniques

Factor analysis involves judgmental decisions that affect the final solution. Decisions have to be made regarding the factorability of data, extraction method, number of factors to be retained, rotation method and so on. For example, different methods can be used to initially extract factors including principal component, image factoring, maximum likelihood methods. Also, different types of rotation can be employed, including orthogonal rotations, such as varimax, quartimax, and equamax, and oblique rotations, such as direct oblimin and promax. Therefore, it should not be surprising that different factor analysts reach different solutions using the same data set. The methods, procedures, and criteria of factor analysis used in this study are summarised in Table AI, together with references providing further detail if required.

Table AI.
Factor analysis criteria employed in the current study

Issues	Technique/test	Criteria	Reference
Factorability of data	1. Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) 2. Bartlett's test of sphericity	Min. acceptable level (0.5) $p < 0.05$	Kinnear and Gray, 2000 Field, 2005
Extraction method	Principal components	Most commonly used Produces more easily interpretable results	De Vaus, 2004
Number of factors to be retained	1. Kaiser's criterion (eigenvalue rule) 2. Scree plot	Eigenvalue ≥ 1.0 Cut-off point: the point where the curve breaks/influxes	Bryman and Cramer, 2005 Field, 2005
Rotation method	Orthogonal/varimax	Solution produced: Has less cross-loaded items Clear and easy to interpret	Pallant, 2005
Ascribing an item to a factor	1. Statistically 2. Conceptually	Min. loading of 0.4 Non contrasting items	Stevens, 1992; Hair *et al.*, 2005 Mahoney *et al.*, 1995

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