The Impact of Big Data Adoption on SMEs Performance

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Abstract

The notion of Industry 4.0 encompasses the adoption of new information technologies that enable an enormous amount of information to be digitally collected, analysed, and exploited in organizations to make better decisions. Therefore, finding how organizations can adopt big data components to improve their performance became a relevant research area. This issue is becoming more pertinent for SMEs. This study investigates the impact of big data adoption on SMEs performance by obtaining the required data from experts. The quantitative investigation followed a mixed approach, including survey data from 224 managers from Iranian SMEs, and a SEM methodology for the data analysis. Results showed that 12 factors affected the BDA in SMEs. BDA can affect both operational performance and economic performance, there has been no support for the influence of BDA and economic performance on social performance. Finally, the study implications and findings are discussed alongside future research avenues and limitations.

1. Introduction

In recent years industries are shifting towards the age of Industry 4.0 or digital transformation. This transformation results from contributions from various engineering and manufacturing disciplines and merging the technologies, including artificial intelligence and machine learning, neuro-technologies, mobile and cloud computing, sensing, and other “exponential technologies”. In the era of Industry 4.0, growing exponentially, data significantly impact obtaining new knowledge, fostering business innovation, and achieving competitive advantage. Accordingly, the utilization of big data with distinct capabilities, features, and specifications has grown rapidly in industrial contexts because of engineering developments and, more specifically, in computer science and information technology. Big data with developing data mining techniques supports the so-called smartness of everything everywhere by facilitating real-time, dynamic, self-adaptive, and precise control capabilities (Ramezani & Camarinha-Matos, 2019; Kopanakis, Vassakis, & Mastorakis, 2016; Chatterjee, Fomasiero, Ramezani & Ferrada, 2019).

Theoretically, there is a wide-ranging discussion about the impact of information technology (IT) on the organization's performance. Although in such a trend, IT contributes to firms' competitiveness, but its role is still relatively unclear (Kohli, & Grover, 2008). In conditions that information flows in the internet and virtual networks are established with high speed and intensity, the level of information of individuals as the main audiences of this data flow is affected by this trend. Thus, the emergence of new ideas and creativity from each person and staff (Bondarouk & Ruel, 2009) and consequently, the necessity creation of a new structure for the current organizations in the global society is inevitable and worthy of serious review and contemplation.

In addition to the hardware available in each job system that requires to be updated in line with the current turbulent era, the software related to each job also needs to be reviewed and updated. On the other hand, “Knowledge management cycle (KMC)” models became essential issues for organizations in the volatile and globalized word in order to make valuable decisions and achieve business outcomes. KMC is a strategic tool in fostering the (symbiosis of implicit and explicit) knowledge and creating a proper perception of it in organizations (Kopanakis, Vassakis, & Mastorakis, 2016).

Big data is one of the topics that has been considered by managers and decision-makers nowadays due to the high speed and volume of data exchange to develop productivity in industries (Nasrollahi, & Ramezani, 2020). Although, in recent years, several studies have been conducted on various methods of data analysis and storage, particularly in the field of industry, and big data has become an important issue in different sectors (Yadegaridehkordi et al., 2020). Still, in small and medium enterprises (SMEs), less attention has been paid to it, and it is a relatively unknown issue for the managers of these organizations. Nevertheless, studies have shown that technology and innovation are strategic priorities for SMEs' growth, and among them, big data will be one of the main drivers (Sen, Ozturk, & Vayvay, 2016).

Since the competitive market becomes more complicated day by day, the organizational decision-makers increasingly rely more and more upon big data for the firm's utilization, understanding process performance, product performance analysis, inventory management optimization, and so on (Hazen et al. 2014). Hence, it is necessary to ensure the quality and reliability of the used data. Lack of adequate and reliable data may lead to inappropriate decisions, missing organizational plans and opportunities, and damage to the organization (Warth, Kaiser, & Kügler, 2011).

Big data adoption (BDA) enables organizations to create a clear picture of customers and their demands in order to make well-informed decisions in designing marketing strategies (Manyika et al., 2011). SMEs, in turn, also require big data to analyse the market and predict customer behavior. Big data in SMEs can lead to increased flexibility, efficiency, responsiveness, and the ability to anticipate and meet customer needs, thus providing organizations a competitive edge (Sen et al., 2016). Adoption of big data is dependent upon technological, organization, managerial, and environmental factors and positively influences firm performance (Frisk & Bannister, 2017; Verma & Bhattacharyya, 2017).

Notably, developed countries have conducted most research on BDA, so we need more studies in developing countries (Baig, Shuib, & Yadegaridehkordi, 2019; Brock & Khan, 2017; Yadegaridehkordi et al., 2020). Therefore, in the present study, we try to evaluate the impact of big data adoption on SMEs' performance in developing countries, an issue that has not been studied yet.

Thereupon, in this study, besides developing a comprehensive model and describing how big data components affect performance, it is helped formulate theoretical basics in this field and confirm previous studies. Generally, one of the aims of this study is to demonstrate the importance of adopting big data in SMEs as a strategic requirement. To achieve this goal, the remainder of this article is structured as follows. The second section provides a brief overview of the theoretical basis and related works in the literature to achieve this goal. The third section describes the research method, statistical population, and the samples under study. In the fourth section, the research findings are presented. Finally, in the last section, the conclusion and suggestions for further research are presented.

2. Literature Review

They provide a base for future Big Data research for SMEs by investigating critical potentials and threats that need to be addressed. Also, they suggested potential practices to seize the full potential of Big Data in SMEs (Sen, Ozturk, & Vayvay, 2016). A study showed that companies that developed technological and managerial capabilities of BDA perform better than other companies (Ferraris, Mazzoleni, Devalle, & Couturier, 2019). In another study, it was stood out that good infrastructure is the most critical factor for big data adoption (Silva et al., 2019). Sun et al. (2018), by content analysis, first identified 26 factors affecting big data adoption in firms and then provided a framework to help decision-making about BDA in organizations. Another study studied the adoption rate of big data in the US SMEs, which its results show that SMEs are very interested in using business analytics. Tian, Hassan, and Razak (2017) reported that BD could be a source of economic strength in the future as the development of BD has changed China's financial markets by creating a variety of financial and monetary services and tools. They predicted that existing structures would undergo serious changes.

Al Tawara and Gide (2016) investigated the effects of "mobile technology (MT)" and "big data-based social media marketing (SMM)" adoption in Jordanian SMEs. They conducted a review of MT practices using SMM in SME organizations to determine various variables that could impact the success of Big data-based social media platforms adoption in SMEs. Another study examined the importance of big data in the "data-driven innovation orientation" of organizations. The results showed that the knowledge generated from big data processes improves organizational performance and enables organizational decision-makers to resolve issues innovatively (Kopanakis, Vassakis, & Mastorakis, 2016).

Following a hybrid approach using data collection with a survey of managers and three case studies, Mikalef, Boura, Lekakos, and Krogstie (2019) studied various resources and contextual factors that drive performance increases due to investing in big data analytics. Finally, applying a "fuzzy-set qualitative comparative analysis" method, four different patterns of components in big data analytic resources were identified that lead to high performance. The impact of big data analytics on Romanian companies' supply chain performance was studied by Oncioiu et al. (2019). Also, there have been some challenges, such as identifying new tools and technologies such as cloud computing and security technologies that companies, to achieve proper performance within the supply chain, are intended to implement.

Maroufkhani et al. (2019) provided a systematic review of big data analytics studies to identify various factors that influence big data adoption on organizations and determine different performance types that big data may improve. Mbassegue, Escandon-Quintanilla, and Gardoni (2016) discussed how big data would enable SMEs to improve their competitiveness and performance and the challenges they might face when adopting these technologies. In another study, the researchers identified barriers preventing SMEs from the successful adoption of big data and proposed a maturity model for SMEs as a roadmap to structure data analytics (Coleman, Göb, Manco, Pievatolo, Tort-Martorell, & Reis, 2016).

Despite the growing number of studies on big data adoption and firm performance, there are lacking in attempts to evaluate the impact of BDA on SMEs' performance; therefore, the present study can help to develop existing knowledge in this field.

3. Research Methodology

In attempt to create the conceptual research model (Fig. 1) the related literature, particularly research conducted by (Ogbuokiri, Udanor, & Agu, 2015; Kopanakis, Vassakis, & Mastorakis, 2016; Sen, Ozturk, & Vayvay, 2016; Anwar, Khan, & Shah, 2018; Ferraris, Mazzoleni, Devalle, & Couturier, 2019; Mikalef, Boura, Lekakos, & Krogstie, 2019; Oncioiu et al., 2019; Maroufkhani et al., 2019), have been studied. Finally, according to our previous work (Nasrollahi and Ramezani 2020), it was found that 51 factors in 12 groups affect the big data adoption in organizations. Table 1 provides definitions of the constructs used in the model. Therefore, in the proposed model, first, the impact of this group of factors on big data adoption is tested. Then the big data adoption effect on organizational performance is investigated. In this model, big data components are independent variables, and organizational performance variables, including economic performance (ECP), operational performance (OPP), social performance (SOP), and organizational performance (ORP) are dependent variables. However, the organizational performance variable is defined as the final dependent variable in the model.

Table 1
Constructs description

Construct	Definition
Feature factors (FEF)	Including: Trainability, Perceived simplicity, Observability, Complexity, and Data quality and integration.
Organizational factors (ORF)	Including: Organizational data environment, Business strategy orientation, Firm size, and Industry type.
Utility factors (UTF)	Including: Perceived compatibility, Appropriateness, Perceived benefits (advantage), Relative advantage, and Perceived usefulness.
Technological factors (TEF)	Including: Technology readiness/ technology resources, Wireless technology, Availability of big data tools, Internal versus external technologies, IS competence/IT structure (infrastructure), Technological capability, and Network challenges.
Stakeholders factors (STF)	Including: Vendor support, Competitive (Perceived industrial) pressure, Government support, laws and policy, Trading partner adoption/ readiness, and IS fashion.
Financial factors (FIF)	Including: Perceived financial readiness, Perceived cost, and Cost of adoption.
Processing factors (PRF)	Including: system integration, Security and privacy, Data control, Predictive analytics accuracy, and Interpret unstructured data.
Cultural factors (CUF)	Including: Organizational (learning) culture, information security culture, and Decision-making culture.
Wisdom factors (WIF)	Including: IT expertise, Knowledge about big data, and big data awareness.
Environmental factors (ENF)	Including: Supply chain connectivity, Risks of outsourcing, Market turbulence, and Marketing and inventory.
Managerial factors (MAF)	Including: Leaders' attitude towards change, Management support for big data, Change efficacy, and Willingness to change.
Skills factors (SKF)	Including: Human resources, Staffing, and Training.
Economic performance (ECP)	Economic performance reflects the firm's ability to reduce costs associated with purchasing materials, energy consumption, waste management, environmental fines, etc. (Green Jr, Zelbst, Bhadauria, & Meacham, 2012).
Operational performance (OPP)	Operational performance (OPP) is related to the firm's capability to increase product distribution efficiency to customers (Zhu, Sarkis, & Lai, 2008).
Social performance (SOP)	Social performance (SP) reflects the status of organizational beliefs about social responsibilities, social accountability methods, policies, plans, and the evident outcomes associated with the organization's social relationships (Younis, Sundarakani, & Vel, 2016).
Organizational performance (ORP)	Financial and marketing and performance of the organization compared to the industry average (Green, & Inman, 2005).

Based on the literature review and conceptual model shown in Fig. 1, this study aims to test 20 hypotheses.

H1: Feature factors have a positive and direct impact on BDA.

H2: Organizational factors have a positive and direct impact on BDA.

H3: Utility factors have a positive and direct impact on BDA.

H4: Technological factors have a positive and direct impact on BDA.

H5: Stakeholders factors have a positive and direct impact on BDA.

H6: Financial factors have a negative and reverse impact on BDA.

H7: Processing factors have a positive and direct impact on BDA.

H8: Cultural factors have a positive and direct impact on BDA.

H9: Wisdom factors have a positive and direct impact on BDA.

H10: Environmental factors have a positive and direct impact on BDA.

H11: Managerial factors have a positive and direct impact on BDA.

H12: Skills factors have a positive and direct impact on BDA.

H13: BDA has a positive and direct impact on operational performance.

H14: BDA has a positive and direct impact on environmental performance.

H15: BDA has a positive and direct impact on social performance.

H16: Environmental performance has a positive and direct impact on operational performance.

H17: Environmental performance has a positive and direct impact on social performance.

H18: Environmental performance has a positive and direct impact on organizational performance.

H19: Operational performance has a positive and direct impact on organizational performance.

H20: Social performance has a positive and direct impact on organizational performance.

Evaluation items and validation of components affecting big data adoption and performance in the questionnaire have been extracted from various studies.

All items were rated on a 7-point Likert scale from 1 (completely disagree) to 7 (completely agree). In this study, field data drawn from an electronic questionnaire focusing on small and medium enterprises (SMEs) in Iran have been used. Therefore, this study's population consists of all senior managers and middle-level managers working in SMEs in Iran, who answered the questionnaires via email. Using the information available in the existing social network databases about experts and specialized such as industrial and scientific associations, irexpert.ir, LinkedIn, etc. a total of 2863 emails have been sent in April 2020. During one month, 836 questionnaires were received, which among them, 612 were removed due to incompleteness. Finally, 224 senior and middle managers completed the questionnaire indicates that the response rate is %7.8.

4. Results And Discussion

Table 2 represents the demographic characteristics of the samples.

Table 2
Sample demographics

Characteristic		N	%
Gender	Male	187	83.5
	Female	37	16.5
Age	Less than 30	33	14.7
	31–40	64	28.6
	41–50	88	39.3
	More than 50	39	17.4
Work experience	Less than 10	54	24.1
	11–20	78	34.8
	21–30	69	30.1
	More than 30	23	10.3
Job title	Chief executive officer	19	8.5
	Chief operating officer	31	13.8
	Factory manager	41	18.3
	Marketing and sales manager	24	10.7
	Purchase manager	30	13.4
	Product manager	10	4.5
	Logistic manager	18	8.0
	Supply chain manager	25	11.2
	Chief information officer	26	11.6
Total		224	100

Table 3 shows the different industries in which respondents are working there. Respondents were from 20 various sectors.

Table 3
Sample industry

Description	N	Percentage
Food and Kindred Products	27	12.1
Food and Kindred Products	16	7.1
Water, Sewer, Pipeline & Power Line	3	1.3
Electrical equipment and component manufacturing	6	2.7
detergent, cosmetic and hygienic products	22	9.8
sanitary ware	5	2.2
automotive parts manufacturing	16	7.1
Medical equipment manufacturing	7	3.1
Machine-Made Carpets manufacturing	3	1.3
Textile mills	3	1.3
Tobacco Products manufacturing	4	1.8
Lumber & Wood Products manufacturing	7	3.1
Office Furniture manufacturing	10	4.5
Papers & Allied Products manufacturing	6	2.7
Chemicals & Allied Products manufacturing	17	7.6
Pharmaceutical Preparations manufacturing	12	5.4
Plastics, Rubber and Synth Resins manufacturing	21	9.4
Concrete, Gypsum & Plaster Products manufacturing	10	4.5
Leather & Leather Products manufacturing	12	5.4
Transportation equipment manufacturing	17	7.6
Ownership Private	138	61.7
Government and Semi-Government	86	38.4
Total	224	100

Prior to the hypothesis test, kolmogorov-Smirnov (K-S) test was performed to evaluate the data's normality at the significance level of %5. As indicated in Table 5, the significance level for all structures is greater than %5. Thus, all data are normally distributed, and it is possible to use the structural equation modelling for the hypotheses test. Furthermore, Table 4 shows the mean and standard deviation of each variable and Cronbach Alpha value for measuring the validity of the questionnaire.

Table 4
Normality (K-S) test, Descriptive statistics, and Validity test

Construct	N	K-S	Sig.	Number of items	Mean	Standard deviation	α	Composite reliability (CR)	Average Variance Extracted (AVE)
Feature factors	224	2.107	0.358	5	3.084	1.093	0.755	0.849	0.693
Organizational factors	224	1.982	0.382	4	3.407	1.002	0.983	0.760	0.601
Utility factors	224	1.838	0.083	5	3.826	1.078	0.907	0.852	0.527
Technological factors	224	2.005	0.237	7	3.152	0.933	0.834	0.780	0.592
Stakeholders factors	224	2.409	0.192	5	3.333	0.980	0.927	0.822	0.679
Financial factors	224	2.080	0.261	3	3.457	0.964	0.947	0.795	0.685
Processing factors	224	1.567	0.211	5	3.517	1.239	0.944	0.860	0.773
Cultural factors	224	2.333	0.307	3	3.621	1.005	0.941	0.796	0.639
Wisdom factors	224	1.585	0.370	3	3.784	0.927	0.979	0.853	0.825
Environmental factors	224	1.699	0.426	4	3.419	1.141	0.818	0.922	0.698
Managerial factors	224	2.144	0.255	4	3.678	1.107	0.906	0.741	0.705
Skills factors	224	2.180	0.291	3	3.606	1.159	0.829	0.931	0.820
Economic performance (ECP)	224	1.600	0.435	6	3.114	0.954	0.753	0.819	0.541
Operational performance (OPP)	224	2.371	0.283	5	3.829	1.208	0.758	0.814	0.674
Social performance (SOP)	224	1.953	0.253	5	3.458	1.095	0.883	0.725	0.766
Organizational performance (ORP)	224	1.836	0.118	7	3.804	1.078	0.877	0.793	0.575
Confirmatory factor analysis (CFA) was performed to validate the factors affecting big data adoption and performance. According to Du, Yalcinkaya, and Bstieler (2016), elliptical reweighted least squares (ERLS) estimation is used in this study because it provides an unbiased estimate of normal and non-normal data. The ERLS chi-square is 234.84. other fit statistics are shown in Table 5 that all indicate proper fit.									

Table 5
Model Fit Statistics

Criterion	χ^2	RMSEA	GFI	AGFI	NFI	NNFI	CFI
Result	234.84	0.041	0.961	0.957	0.973	0.935	0.942

Because of the large number of constructs and the small sample size, the proposed conceptual model has been evaluated using the structural equation modelling method. LISREL 9.30 software was used to complete both the confirmatory factor analysis required to appraise the measurement model and the structural analysis needed to assess the structural model due to the significant model fit information existing.

Table 5 shows a summary of descriptive statistics. All the correlation coefficients shown in Table 6 are significant at the %1 significance level.

Table 6
Correlation coefficient matrix

	FEF	ORF	UTF	TEF	STF	FIF	PRF	CUF	WIF	ENF	MAF	SKF	ECP	OPP	SOP	ORP
FEF	0.882															
ORF	0.380	0.829														
UTF	0.291	0.612	0.812													
TEF	0.273	0.391	0.399	0.880												
STF	0.471	0.412	0.482	0.726	0.840											
FIF	0.516	0.614	0.464	0.647	0.631	0.823										
PRF	0.440	0.454	0.690	0.642	0.584	0.439	0.781									
CUF	0.500	0.712	0.578	0.471	0.489	0.575	0.347	0.796								
WIF	0.451	0.546	0.559	0.635	0.531	0.567	0.353	0.561	0.814							
ENF	0.542	0.318	0.632	0.598	0.402	0.346	0.317	0.434	0.555	0.826						
MAF	0.380	0.496	0.720	0.634	0.432	0.343	0.509	0.678	0.315	0.420	0.790					
SKF	0.428	0.631	0.694	0.450	0.328	0.515	0.458	0.436	0.612	0.575	0.490	0.874				
ECP	0.628	0.701	0.590	0.506	0.412	0.469	0.585	0.502	0.477	0.501	0.619	0.433	0.819			
OPP	0.227	0.563	0.448	0.409	0.641	0.457	0.632	0.559	0.429	0.463	0.559	0.340	0.332	0.834		
SOP	0.589	0.538	0.527	0.485	0.418	0.308	0.596	0.429	0.306	0.403	0.367	0.452	0.570	0.497	0.803	
ORP	0.519	0.607	0.376	0.373	0.531	0.475	0.337	0.399	0.320	0.480	0.424	0.510	0.4000	0.362	0.312	0.822

Table 7 shows the results of the hypotheses test. The research model has been approximately accepted, and only two hypotheses rejected. The hypotheses H1 to 12 have been accepted in the first set, which indicates the impact of all identified factors on BDA. Acceptance of H13 and H14 reflects the influence of BDA on improving the organization's operational and economic performance. But, by rejecting H15, the impact of BDA on improving social performance cannot be verified. Approval of H16 shows the direct effect of ECP on operational performance. The study's findings do not approve the positive and significant impact of ECP on SOP, and for this reason, the H17 is rejected. Also, ECP has a positive and significant impact on ORP, and thus the H18 is verified. Finally, the H19 and H20, which indicated a direct and meaningful relationship of OPP and SOP with ORP have also been accepted as expected.

Table 7
Structural model results

Research Hypothesis	Beta coefficients	Status	Research Hypothesis	Beta coefficients	Status
H ₁ FEF → BDA	0.27**	Supported	H ₁₁ MAF → BDA	0.50**	Supported
H ₂ ORF → BDA	0.39**	Supported	H ₁₂ SKF → BDA	0.31**	Supported
H ₃ UTF → BDA	0.37**	Supported	H ₁₃ BDA → OPP	0.22**	Supported
H ₄ TEF → BDA	0.29**	Supported	H ₁₄ BDA → ECP	0.27**	Supported
H ₅ STF → BDA	0.54**	Supported	H ₁₅ BDA → SOP	0.09	Not Supported
H ₆ FIF → BDA	0.49**	Supported	H ₁₆ ECP → OPP	0.28**	Supported
H ₇ PRF → BDA	0.47**	Supported	H ₁₇ ECP → SOP	0.13	Not Supported
H ₈ CUF → BDA	0.40**	Supported	H ₁₈ ECP → ORP	0.43**	Supported
H ₉ WIF → BDA	0.38**	Supported	H ₁₉ OPP → ORP	0.39**	Supported
H ₁₀ ENF → BDA	0.52**	Supported	H ₂₀ SOP → ORP	0.59**	Supported

5. Conclusion

Considering the rapid increase in volume and complexity of data due to the emerging advanced technologies and diversity of markets, paying attention to data acquisition and analysis has become an inevitable organizational approach. This issue is becoming more pertinent for SMEs, especially in developing countries that encounter limited resources and infrastructures. Accordingly, this study aimed to evaluate the impact of BDA on SMEs' performance. The

literature was first reviewed to achieve this goal, and the most critical factors affecting BDA from previous studies were identified. In the next step, the impacts of BDA on performance were evaluated by obtaining the required data from experts.

This study yields valuable results by identifying the impacts of BDA on SMEs organizational performance. As summary, economic performance has a direct and positive impact on operational and organizational performance but has no significant effect on the organization's social performance. Finally, operational and social performance has a positive and significant impact on organizational performance. These results indicate that to improve various organizational performance such as ENP, OPP, SOP, and ORP, the senior management has to commit to BDA.

This study highlights the importance of understanding the BD's potential benefits for better decision-making and performance improvement because using BD creates many strategic and profitable opportunities for SMEs to succeed in a business ecosystem where competitiveness and innovation are key drivers. BD is a new opportunity for SMEs to use new data types to improve organizations' agility and solve complex problems and achieve better results and performance. As a result, fundamental changes occur in organizations' operations and performance, and consequently, organizations move towards more accurate and better information-based decision-making and modelling. Therefore, using BD is a crucial resource for SMEs to create value, new knowledge, and new processes and products.

The findings of this study provide managers a practical framework for decision-making about BDA. It can also be useful for managers and entrepreneurs, namely by offering them effective strategies and tips they can adopt and prioritize to improve the organizational performance. For instance, they can see how the various components of Big data affect an organization's performance. Researchers also may use this study to investigate various relevant hypotheses and improve the accuracy of future studies. Future research can develop variable measurement scales to validate the proposed model. As this model is likely one of the first models which evaluates the impact of BDA on SMEs Performance comprehensively, re-evaluating the model using data obtained from various samples could be interesting.

In this study, two major limitations could be addressed in future research to obtain more reliable results. In this study, mediator and moderator variables such as financial resources have not been investigated, and therefore other researchers can consider mediator and moderator variables. Also, variables such as industry type, organization size, and employee number can be regarded as control variables.

Abbreviations

SME:	Small and medium enterprise
BDA:	Big data adoption
IT:	Information technology
KMC:	Knowledge management cycle
SMM:	Social media marketing
ECP:	Economic performance
OPP:	Operational performance
SOP:	Social performance
ORP:	Organizational performance
FEF:	Feature factors
ORF:	Organizational factors
UTF:	Utility factors
TEF:	Technological factors
STF:	Stakeholders factors
FIF:	Financial factors
PRF:	Processing factors
CUF:	Cultural factors
WIF:	Wisdom factors
ENF:	Environmental factors
MAF:	Managerial factors
SKF:	Skills factors
ECP:	Economic performance
OPP:	Operational performance
SOP:	Social performance
ORP:	Organizational performance

Declarations

Availability of data and materials

Not Available.

Competing interests

The authors declare no conflict of interest.

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Authors' contributions

Mahdi Nasrollahi, Javaneh Ramezani & Mahmoud Sadraei: conceptualization; methodology; data analysis; writing, reviewing and editing.

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Figures

Figure 1

Conceptual model