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Research Article

An Investigation on the Impact of Business Intelligence over the Performance of Startup Companies according to Innovation and Knowledge Management as Mediators

Farzad Nazari,[1] **Seyedeh Safiyeh Taghavi**,[2] **Esmaeil Valizadeh**,[3] **Mehrdad Soleymani**,[4] **Danial Shahrabi Farahani**,[5] **and Raana Bagheri**[6]

[1]*Department of Management, Payame Noor University, Tehran, Iran*
[2]*Department of Management, Alzahra University, Tehran, Iran*
[3]*Faculty of Economics and Accounting, Islamicazad University-South Tehran Branch, Iran*
[4]*Institute for Management and Planning Studies (IMPS), Tehran, Iran*
[5]*Master of Marketing Management, University of Tehran, Faculty of Management, Tehran, Iran*
[6]*Department of Management, Science & Technology, Amirkabir University of Technology (Tehran Polytechnic), ZakariayaRazi Bul, Tehran, Iran*

Correspondence should be addressed to Raana Bagheri; raana_bagheri@aut.ac.ir

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Value-Originality. Startup companies look for solutions to remove useless issues and enhance the activities offering value adding over the product/service development stage in such a way that such companies will be able to provide great products and more probabilities for success with no need to employ considerable investments from external sources. Accordingly, innovation, business intelligence, and knowledge management will contribute to the positive findings of startup companies. *Objectives*. Hence, the purpose of the present study was to conduct an investigation on the impact of business intelligence over the performance of startup companies according to such mediators as innovation and knowledge management. *Methods*. The type of this study is correlation and is also an applied and descriptive-survey work regarding objective and data gathering. Our statistical population encompassed all related experts and managers in the following Iranian startups: Pinket, Alibaba, Snapp, Filimo, IDPay, PhonePay, TapSell, and Body Spinner. Our sample was composed of 108 experts and managers in mentioned companies, who were chosen based on the cluster sampling method. Structural equation modeling with partial least squares approach was used to analyze the gathered data. *Findings*. Our results reveal the effectiveness of business intelligence, innovation, and knowledge management on the performance of startups and that of business intelligence on innovation and knowledge management. Ultimately, innovation and knowledge management are mediators of the relationship between business intelligence and performance of startups. *Conclusion*. The startup companies' managers are strongly recommended to take advantage of innovation and knowledge management in order to enhance the performance of their businesses.

1. Introduction

Over the last two decades, there have been many contents and qualitative changes in global markets, and thus, the movement towards regionalization and globalization of markets has accelerated. In parallel, the production-oriented period is coming to an end, and the customer-centric period is taking shape. Industrial producers, with the aim of making the best use of facilities and preventing the waste of valuable resources, have devised measures that resulted in a revolution at the industrial structure. One of the obvious and main characteristics of this structural revolution is the further growth and promotion of small and medium-sized enterprises (SMEs). SMEs play an important role in the

economic and social development of countries. In all economies, these groups make up the vast majority of the firms and are usually responsible for creating jobs in the community, while one-third to two-thirds of the volume of private sector transactions take place in these companies. In addition, SMEs are referred to as safe and reliable markets in the world, which are considered as a place for micro and small businesses to operate on a larger scale. Experts believe that SMEs are able to manage the world's economies with a high power of competitiveness and productivity [1, 2].

Besides, in order to make able organizations react quickly to market changes, they need management information systems which can provide different cause and effect analyses of the organization and its environment. On the one hand, business intelligence systems, which are among the most sophisticated information systems available, provide the means by which an organization's information needs can be adequately met. Business intelligence provides up-to-date reliable business information and enables organizations to reason and understand the concepts hidden in business information through the process of data discovery and analysis [3, 4]. Instant access to such information can help to make accurate decisions and create dynamic changes that will lead to improve the company's core line [5, 6].

On the other hand, knowledge is the main source of competitive advantage in organizations because it provides new opportunities for them such as the opportunity to solve problems using business intelligence [7]. Knowledge management mainly should focus on complete knowledge transferred between individuals and groups by creating business intelligence [3]. Acquiring knowledge and using it in the right way is the only way to enjoy a sustainable competitive advantage in the market, thus achieving performance productivity goals [7, 8, 9].

Furthermore, performance evaluation is considered as one of the most important strategies to effectively enhance an organization. Therefore, for many years, managers and researchers have been trying to provide a suitable solution for evaluating organizations. In the meantime, several methods have been proposed for performance evaluation from the past to the present, including balanced scorecard, quality award patterns, financial performance measurement, performance pyramid model, and performance charter [10, 11].

Today, with the globalization of businesses, organizations seek to maintain markets around the world to improve their competitiveness; hence, the traditional approach cannot be justified because knowledge-based economics have replaced resource-based ones [12]. To this end, a preferable solution is knowledge management. Accordingly, knowledge implementation and sharing will result in the improved integration of startup performance and production efficiency [13]; however, there are many barriers in the implementation of knowledge management in startups' performance [14, 15]. Attitude and desire to learn and share new knowledge is one of the important barriers to prevent knowledge creation [16]. Moreover, the vertical and long hierarchical structure prevents the flowing and sharing of knowledge and communications [17]. Also, what matters is the management of knowledge transfer to central partners, for which communicative barriers may make it difficult within and between different parts of the organization [12, 18, 19].

Additionally, innovation today should be considered as a requirement for any company due to the end of market competition, globalization, and rapid improvement of technology [20]. Companies do innovation to achieve business goals in terms of productivity, performance improvement, quality control, learning, and market development [21]. It refers to new management methods, new organization, new marketing, and new corporate strategies and describes an organization on implementing a new organizational approach in business practices, the workplace, or external relationships [22, 23].

Accordingly, in a study by Saura et al. [24], on the one hand, the following factors were identified as a necessity for the success of startup companies: startup tools, technology-based startup, the attitude of the founders, and the startup methodology development. Also, the following were found to be adversely effective on the performance of startups: the frameworks and programming languages, type of job offers, and the business angles' requirements. On the other hand, some neutral factors were found as follows: the development of the business plan, the type of startup project, and the incubator's and startup's geolocation. Moreover, in another study, some topics were identified as the problems of implementing business intelligence including the main security issues such as malware, cybersecurity attacks, data storing vulnerabilities, the use of testing software in Internet of Things (IoT), and possible leaks due to the lack of user experience [25–27].

Nowadays, on the one hand, due to increasing production costs such as energy and the growing trend of taxes and in general variable costs, and on the other hand, the recession of the construction industry because of declined liquidity and the increased average age of society and current costs, startups have prospered. Obviously, with the measures taken place in the past years, the need to increase production led to the construction and establishment of startup businesses, which gave rise to a competition between manufacturers for business continuity and survival. In order to achieve optimal profit and continue the activity of startup businesses, they need to be present in international markets. Most research studies conducted on the innovation and performance of startups have ignored the business intelligence and knowledge management which are important and key factors. Hence, examining the impact of business intelligence on the performance of startups with the mediating role of innovation and knowledge management will be a key issue for business executives, including manufacturers, marketers, and vendors because considering this dimension will be a vital and guaranteed thing to improve the performance of startups. Due to the lack of such a study in Persian literature, the present study aimed at the investigation of the effect of business intelligence on the performance of startups with the mediating role of innovation and knowledge management. For this purpose, by studying the theoretical and experimental background of the mentioned

subject and considering the results of Caseiro and Coelho [28] and Abbas and Sagsan [29], the following hypotheses were developed for this research:

H1: business intelligence affects the performance of startups

H2: business intelligence affects innovation

H3: business intelligence affects knowledge management

H4: innovation affects the performance of startups

H5: knowledge management affects the performance of startups

H6: innovation mediates the relationship between business intelligence and performance of startups

H7: knowledge management mediates the relationship between business intelligence and performance of startups

By explaining the basic variables of the research topic and establishing a relationship between them based on theoretical and experimental background, the model and conceptual framework of this research was developed. The conceptual model of this research is presented in Figure 1.

The present study is organized as follows: the introduction and representation of the main topics are presented in Section 1. Section 2 presents a literature review of the study. Materials and methods are provided in Section 3, and Sections 4 and 5 present results of data analysis and checking the hypotheses as the discussion, respectively. Finally, the concluding remarks and limitations of this study are presented in Section 6.

2. Literature Review

2.1. Business Intelligence. Most recently, business intelligence has been the largest area of information technology investment in organizations and is recognized as the highest technology priority [30]. A business intelligence system is an integrated set of planned tools, technologies, and products used to collect, integrate, analyze, and publish data. More simply, the main tasks of the business intelligence system include intelligent exploration, integration, and accumulation, and multidimensional analysis of data from various information sources [31]. This definition implicitly states that data are treated as a very valuable collective resource which are translated from quantity to quality [32]. Therefore, meaningful information can be presented at the right time, the right place, and the right way [33] to help individuals, offices, departments, or even larger units facilitate improved decision making [34]. Recently, the implementation and deployment of business intelligence systems have become one of the main priorities of senior information managers of organizations [35]. According to Schiff [36], implementing a business intelligence system in an organization helps to improve the overall productivity and effectiveness of an organization; then, the organization will have better decision-making capability about potential issues occurring in exceptional circumstances. It also allows business users to better analyze and understand their organization's plans and results. However, there is evidence that a significant number of companies have failed to realize the expected benefits of business intelligence. And even some people sometimes think that the actions of the business intelligence project are a failure in themselves [37].

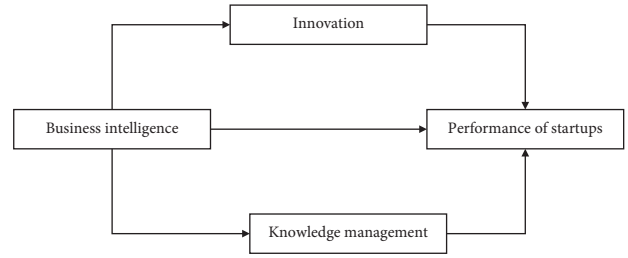

Figure 1: The conceptual model of the present study.

2.2. Iranian Startup Performance. Distinctive elements in startups include innovation, digital solutions, and scalability, according to which the risk management of such businesses requires a special approach [38]. An increase in the number and variety of creative products can be seen in recent years, followed by the emergence of startups. Also, along with the abundant growth of startup businesses in Iran and lifting of sanctions, various activities have been carried out including the entrance of foreign investment companies, launching associations to support startup businesses, inviting Iranian investors, and creating a suitable space for business elites and investors [39].

Given the specific conditions in Iran, such as the young population, increased penetration of digital media, the level of access and desire for new technologies at the youth level, and most importantly, the employment problem, the followings are some of the reasons to justify the importance of startups:

(i) Linking startups with knowledge creation and its effect on the national development process

(ii) Helping the transfer and localization of knowledge and technology in the country

(iii) Diversification of national sources of income (production)

(iv) Diversification of economic investment fields in the country

(v) Investing for the growth of the country's capital and human resources in the knowledge/technology-based fields

(vi) Power and the possibility of high and rapid growth of startups in comparison with other sectors

(vii) Promoting the creativity, invention, and innovation culture and strengthening the process of commercialization and conversion of knowledge into a product with high economic value

(viii) The impact of the growth of this culture on reducing the level of unemployment among youth, public participation in solving the problem of employment, and growth and creation of job opportunities in the country

2.3. Knowledge Management. Knowledge is a key factor in the emergence of creativity in the organization, and from this angle, managing organizational knowledge and assessing its status in the organization are important and necessary [40]. Knowledge management is a process that helps organizations to retrieve, select, organize, disseminate, and transmit specialized information that is essential for such activities as problem solving, dynamic learning, strategic planning, and decision making [41]. Knowledge management in the organization is also considered as a competitive advantage for the organization [42], focusing on the processes of creating, disseminating, and utilizing knowledge (Patil et al., 2019). In any organization, the five key factors affecting the implementation of knowledge management include culture, human resource management, leadership, information technology, and control [43]. Accordingly, a desirable knowledge management situation in the organization leads to the emergence of creativity and innovation [44].

2.4. Innovation. Innovation is one of the vital factors for the success of organizations, which is often known as the representation and conscious application of ideas, processes, products, or procedures that are new to different parts of the organization, and its acceptance will be significant for an organization to create value [45]. What matters in explaining the concept of innovation is to emphasize innovation not as a one-dimensional concept but a multifactorial domain including a set of different dimensions [46]. Currently, innovations provide a mechanism by which business entities maintain their position in the market. Organizational innovation is a way of adapting to the environment. From this perspective, innovation means that business entities must make more efforts to adapt to the environment since organizational innovation affects the financial performance of a company [47].

2.5. Business Intelligence and Performance of Startups. Today, business intelligence systems are widely used in many areas of business which aim to make value-creating decisions. However, to help this area reach its full potential, activists and researchers need to fully understand the processes by which startups can create value through business intelligence [48]. The use of business intelligence in businesses and its proven impact as a solution to problems have shown the value and importance of this concept in various sectors of industry and services [49]. In doing so, although big data helps companies gain a competitive edge over competitors in many ways, big data analysis still faces many challenges [50]. Through big data analysis, business intelligence can help companies improve customer satisfaction, risk management, competitive intelligence generation, important decisions, and price optimization [51].

2.6. Business Intelligence and Knowledge Management. In this day and age, commercial companies have to create and maintain a competitive advantage in order to survive and increase market share. Meanwhile, companies that use knowledge to emphasize their identification ability will be more successful. The organizations have realized that acquiring knowledge and using it properly is the only way to have a sustainable competitive advantage in the market. Hence, knowledge is recognized as a strategic resource that needs to be managed in order to improve the competitive performance of the organization [52]. Knowledge management has been discussed by several researchers in terms of capabilities of the knowledge recognition process, knowledge creation, knowledge storage and retention, knowledge sharing, and knowledge application [53]. The knowledge management should mainly focus on perfect knowledge which is transmitted between individuals and groups in the context of business intelligence [54]. Knowledge management and business intelligence are both based on information technology, relying on the Internet, hardware and software, and database technology. Both involve the collection, organization, sharing, and use of knowledge and information. Knowledge management and business intelligence interact and complement each other, focusing mainly on recognition. On the one hand, knowledge management pays special attention to those having good knowledge and high culture. Knowledge management also emphasizes the importance of knowledge acquisition and its effective use.

On the other hand, business intelligence focuses on technology and data, that is, the skill of a user who normally uses quantitative analysis of a technical expert to solve business problems relying on the business intelligence system. Business intelligence and knowledge management have a high value in promoting decision making and improving organizational performance; they are considered as essential tools for modern organizations. Business intelligence and knowledge management employ knowledge to improve decision making. There is still ambiguity as to whether knowledge management is a part of business intelligence or vice versa. This ambiguity stems from the definition of these concepts. Business intelligence focuses on explicit knowledge, but knowledge management emphasizes both explicit and implicit knowledge (Cheng and Cheng, 2011).

2.7. Innovation and Performance of Startups. Startups are built around innovative and creative ideas. In fact, brainy people with new ideas are looking for ways to monetize their ideas and deliver products or services based on those ideas. Startups are usually based on risky ideas whose business model is not clear and their target market is hypothetical; therefore, they have lower savings costs, high risk, and high potential return on investment [55]. Startups face many challenges during the production of their products. However, with effective management methods, many of these challenges can be anticipated and solutions can be developed to minimize them [56]. Therefore, a startup is argued to be a

temporary organization looking for a scalable and sustainable business model. Startups need to move forward with risk management as well [57]. To this end, a successful startup has the potential to grow more than a mature company; that is, it can grow with less capital and labor and even can have more growth than older companies [58]. The uniqueness of the benefits of innovation, the organizational characteristics of startups, and the entities entrepreneur and innovator have been the three main factors in the success of startups [59].

2.8. Knowledge Management and Startups' Performance. Knowledge management is a set of activities, initiatives, and strategies employed by companies to produce, store, transfer, and apply knowledge to improve startups' performance [60]. Knowledge management is one of the most important factors for the success of organizations in these changing circumstances and the information age. The importance of this issue is such that today a number of businesses measure their knowledge and reflect it as the intellectual capital of the business and an indicator for ranking companies in their reports [61]. Moving towards knowledge-based environments has considered knowledge management as a key and strategic tool to improve the performance of startups, thus sharing and applying knowledge [62].

2.9. Knowledge Management and Innovation. Organizations currently are forced to have sustainable innovation in management that is created through continuous learning and knowledge sharing among employees and customers. As a matter of fact, managers and policy makers of organizations have found that successful innovation is knowledge based which must be provided in all organizations [63]. Innovation is the factor of production, adaptation, or operation of a value-added initiative in a socioeconomic environment, such as the recreation and expansion of products, services and markets, development of new production methods, and deployment of new management systems [64].

3. Methodology

Since the present study aimed to examine the effectiveness of scientific theories on the impact of business intelligence on the performance of startups with the mediating role of innovation and knowledge management and developed applied knowledge about the quality of the relationship and the impact between variables, it is considered as applied research. Also, because this research was carried out in real situations with large samples, it is a field study in terms of position. In addition, due to studying the relationship and correlation between research variables based on data collection, it is a correlational work as well. In addition, to review the related resources, we undertook a systematic literature review (SLR) [65]. The statistical population of this study included all relevant experts and managers in startup companies, including Pinket (active in online grocery shopping), Alibaba (active in online ticket shopping and travel and accommodation reserving), Snapp (active in online transportation), Filimo (active in providing online video content), IDPay (active in online payment), PhonePay (active in online payment), TapSell (active in digital marketing), and Body Spinner (active in garment shopping), with a total number of 150 companies. Various methods were used to determine the sample size, including the Krejcie and Morgan's table. This table provides the sufficient number of samples for the researcher. Accordingly, the sample consisted of 108 related experts and managers in startup companies, selected by the cluster sampling method. Here, on the one hand, a researcher-made questionnaire was used, which includes 34 questions, of which 8 questions to measure the business intelligence, 8 questions to measure the performance of startups, 9 questions to measure the knowledge management, and 9 questions to measure the innovation were used. The items and queries in the questionnaire were provided on a website, and the corresponding link was given to the respondents through their e-mail so that they could readily choose their desired option in less than 20 minutes. This kind of survey was prepared for the convenience of the experts participating in this study.

On the other hand, there are several methods for assessing the validity of the questionnaire; the most important of which are as follows: content validity, concurrent validity, predictive validity, and construct validity. To this end, we used content validity and construct validity (convergent). To check the content validity of the questionnaire, the questions were given to a number of management professors to comment on the validity of the questionnaire according to the components extracted from previous valid research and with reference to relevant sources. After reviewing and evaluating the questionnaires by professors and experts and making minor corrections, the content validity of the questionnaires was confirmed. Then, the factor loading was used to evaluate the validity of the structure. In performing factor analysis, it must first be ensured that the available data can be used for analysis. In other words, is the number of data desired for factor analysis appropriate? For this purpose, Kaiser–Meyer–Olkin (KMO) index and Bartlett's test are used. Before confirmatory factor analysis, the KMO test should be performed to ensure sampling adequacy.

According to Table 1, the value of sampling adequacy index for each of the variables is above 0.6, and also according to Table 2, the value resulted from the KMO test in the general model is above 0.6. Also, since the significance level of Bartlett's test is lower than the value of research error (0.05), the adequacy of sampling is confirmed.

After ensuring the adequacy of the sample size, the values of the items were examined, and the items whose value was less than 0.3 were excluded from the analysis due to incompatibility with other items and not be a good explanation for that dimension. To measure reliability in this study, in addition to Cronbach's alpha coefficient, the composite reliability index was also calculated. Also, given the suitable conditions of the participants (Table 3) to conduct the analysis, the software Smart PLS was the best

Table 1: Adequacy statistics of the variables.

Variable	Business intelligence	Knowledge management	Innovation	Performance of startups
Sampling adequacy index	0.864	0.878	0.921	0.919
Significance	0.000	0.000	0.000	0.000

Table 2: Adequacy statistics of the general model data.

Sampling quality index	0.859	
Bartlett's test of sphericity	Chi-squared	849.614
	Degree of freedom	36
	Significance	0.000

Table 3: The demographic specifications of the participants.

Variables		Number and percentage
Gender	Male	62 (57%)
	Female	46 (43%)
Marital status	Single	36 (33%)
	Married	72 (67%)
Education level	Bachelor of Science	40 (37%)
	Master of Science	56 (52%)
	PhD	12 (11%)
Age	20–30	18 (17%)
	31–40	69 (64%)
	41–50	21 (19%)

option in order to test the conceptual model. This process was carried out in two general steps including "model's fit examination" and "hypotheses testing." The former has three stages: (1) the measurement model is examined through validity and reliability analyses; (2) the structural model is examined by estimating the path between the variables; and (3) the overall fit of the model is examined. Finally, if the model has a good overall fit in the above three stages, then the research hypotheses can be examined.

4. Results

The demographic specifications of the participants are presented in Table 3.

4.1. Evaluation of Measurement Model

4.1.1. Factor Load coefficients. First, the research model is tested based on factor load coefficients. In the case of the factor load lower than 0.3, the relation is considered as poor and will be ignored. A factor load of 0.3–0.6 is acceptable, and in case of greater than 0.6, it will be very desirable. The structural equation model of the present study in the standard factor load estimation mode is drawn in Figure 2. The results of the test showed that all the factor loads of the indices are above 0.4, and their factor load is desirable.

4.1.2. Cronbach's Alpha Coefficient. This coefficient was invented by Cronbach and is one of the most common methods of measuring the reliability of questionnaires. The reliability of the questionnaire means that if the measured traits are remeasured with the same device, under the same conditions and at different times, the results will be almost the same. In this study, Cronbach's alpha for variables was calculated using Smart PLS software and reported in Table 3. Accordingly, the closer this coefficient is to one, the more appropriate it is. Here, the reliability of the questionnaire about independent and dependent variables was obtained at a very acceptable level.

4.1.3. Composite Reliability. The composite reliability is a more modern criterion than Cronbach's alpha since it calculates the reliability of variables not absolutely but according to the correlation of their indices with each other. If the value of the composite reliability for each variable is more than 0.7, it indicates the appropriate internal stability of the model. The composite reliability of each variable is described in Table 3, where all variables have composite reliability of above 0.7 and above, and therefore, the model is approved in terms of composite reliability as well.

4.1.4. Convergent Validity. The average variance extracted was used to evaluate the convergent validity of the model. This criterion shows the degree of correlation of a construct with its characteristics that the higher this correlation, the greater fit of the model. This index is used in latent variables with the reflective model and is not applied in hybrid models. The average variance extracted is to measure convergent validity where the critical value is 0.5; that is, the average variance extracted above 0.5 indicates acceptable convergent validity. The values of this criterion for the research model are described in Table 4. As it can be seen, the average variance extracted for all variables is greater than 0.5, indicating the convergent validity of the model.

4.1.5. Divergent/Discriminant Validity. In order to evaluate the discriminant validity of the model, Fornell–Larcker [66] criterion was used. This criterion determines the degree to which a variable relates to its variables when compared to other variables so that the acceptable discriminant validity indicates that one variable has more interaction with its indicators rather than with other variables. Fornell and Larcker state that discriminant validity is at an acceptable level when the average variance extracted for each variable is greater than the common variance between that variable and the other variables. In Smart PLS software, this is done by a matrix in which the cells contain the values of the correlation coefficients between the variables and the square root of the mean values of the average variance extracted for each variable. Table 4 presents the matrix corresponding to the variables. The model has an acceptable divergent validity, if the numbers in the main diameter of the matrix are greater than its bottom values. As it can be seen in Table 5, all main

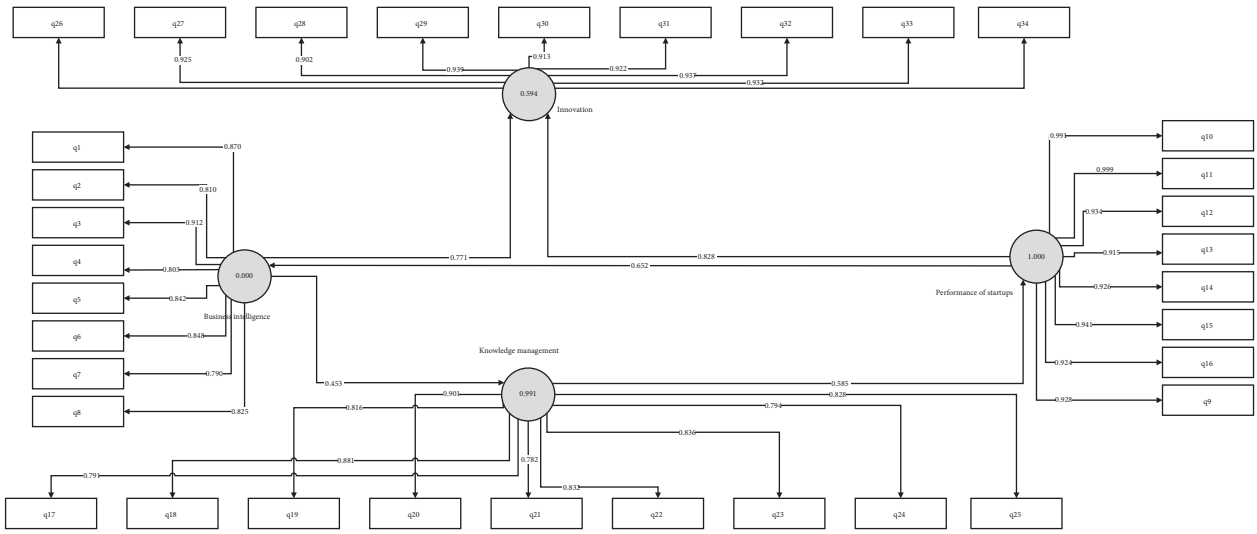

Figure 2: Structural equation model in the standard factor load estimation mode.

Table 4: The results of Cronbach's alpha coefficient, composite reliability, and average variance extracted.

Component	Cronbach's alpha	Composite reliability	Average variance extracted
Business intelligence	0.938	0.949726	0.702917
Knowledge management	0.941	0.951845	0.687584
Innovation	0.978	0.981296	0.853591
Performance of startups	0.976	0.979526	0.856750

Table 5: Divergent (discriminant) validity of the model.

Variable	Business intelligence	Innovation	Knowledge management	Performance of startups
Business intelligence	0.838401			
Innovation	0.770600	0.9236		
Knowledge management	0.795550	0.815235	0.829207	
Performance of startups	0.766130	0.998621	0.808098	0.925608

diameter numbers are larger than their bottom column numbers, indicating acceptable divergent (discriminant) validity of the model.

4.2. Evaluation of the Structural Model. The structural or external model represents the relationships between the latent variables of the model. In fact, in this section, the questions (indicators) are not considered, and only the latent variables along with the relationships between them are examined. In evaluating the structural model, several criteria are used, each of which is discussed below.

4.2.1. T Value. The T value is the most basic criterion for measuring the relationship between variables in the model. If the value of these numbers is greater than 1.96, it indicates the accuracy of the relationship between the variables and thus confirms that relationship(s) is at the confidence level of 95%. Figure 3 depicts the test results of the conceptual model in the significant state of t coefficients. The values calculated on the arrows represent the results of T value which are all greater than 1.96, so it can be concluded that at the significance level of 95%, all questions are considered for the structural equation model and no question needs to be removed.

4.2.2. Coefficient of Determination. This criterion indicates the effect of an independent variable on a dependent one. The coefficient of determination is calculated only for the dependent variable of the model, and in the case of the independent variable, the value of this criterion is zero. The higher the value of the coefficient of determination related to the dependent variable of the model, the better the fit of the model. Chin (1998) represents the three numbers 0.19, 0.35, and 0.67, respectively, as the criteria for weak, medium, and strong values of R^2. If the structures of a given internal path model describe an endogenous latent variable (dependent variable) with a small number (one or two) exogenous latent variables, the coefficient of determination will be acceptable at the intermediate level. However, if the endogenous latent variable depends on several exogenous latent variables, the variable of the coefficient of determination must be at least at

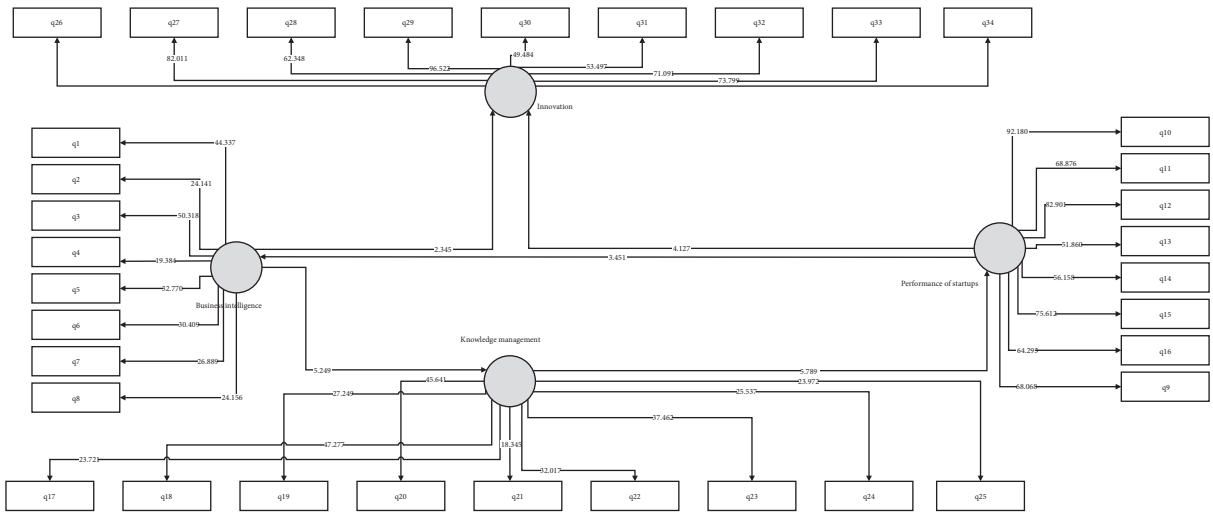

Figure 3: Structural equation model of the research model in the case of significant coefficients of t statistic.

a significant level. Table 5 shows the coefficient of determination values of the dependent variable. As it can be seen, the values have a strong coefficient of determination for the research variables.

4.2.3. Q^2. Another way to evaluate a structural model is to examine the model's ability to predict. The predominant criterion for a predictive relationship is Q^2. This criterion, which is usually measured using the blind folding (BF) method, claims that the model should be able to provide a prediction of endogenous latent variable representations. It should be noted that the BF method is used only for an endogenous latent variable which is operated as a reflective measurement model. Accordingly, if the value of Q^2 for a dependent variable becomes zero or lower, the relationship between the other variables in the model and that dependent variable is not well defined. That is, if this value is greater than zero for a given endogenous variable, their independent variables will have a predictive relationship. Regarding the intensity of the predictive power of the model, three values 0.02, 0.15, and 0.35 have been determined, which, respectively, indicate the weak, medium, and strong predictive power of the model relative to that variable. Given the value of Q^2 obtained for the dependent variables of the model shown in Table 6, it is clear that the predictive power of the model for the dependent variable is at a strong level.

4.3. Evaluation of General Model. The general model includes both the measurement and structural parts, and by confirming its fit, the fitness assessment will be completed in a model. For the overall fit of the model, only goodness-of-fit (GoF) index is used. Since this index is to some extent dependent on the common average, then this index can be used conceptually when the measurement model is reflective.

As mentioned above, the coefficient of determination (R^2), Q^2, and GoF were employed to evaluate the fitness of the structural model and the predictive power of the model, and to measure the overall model, respectively (as shown in Table 7).

Table 6: The common values and coefficient of determination for the dependent variables.

F0E0 Variable	Common values	Coefficient of determination
Business intelligence	0.702917	—
Innovation	0.853591	0.593824
Knowledge management	0.687584	0.991119
Performance of startups	0.856550	0.999964

The GOF value for the model was calculated to be 0.817255, indicating a strong and very suitable overall fit of the model based on which, it is now possible to examine the research hypotheses.

5. Discussion

In this section, each hypothesis is checked according to the results obtained here.

H1: business intelligence affects the performance of startups. In examining the effects of business intelligence on the performance of startups, as it can be seen in Figure 2, the path coefficient is calculated to be 0.652 and given that the T value is 3.451, so it can be concluded that such a path coefficient is significant at the error level of 0.05; that is, business intelligence has a significant effect on the performance of startups, so the first hypothesis is supported and confirmed.

H2: business intelligence affects the innovation. In examining the effects of business intelligence on innovation, as it can be seen in Figure 2, the path coefficient is calculated to be 0.771 and given that the T value is 2.345, so it can be concluded that such a path coefficient is significant at the error level of 0.05; that is, business intelligence has a significant effect on innovation, so the second hypothesis is supported and confirmed.

Table 7: The report of evaluation based on the criteria R^2, Q^2, and GoF.

	R^2			Q^2			GoF		
Variable	0.19 weak	0.33 medium	0.67 strong	0.02 weak	0.15 medium	0.35 strong	0.01 weak	0.25 medium	0.36 strong
Innovation		0.593824			0.502829				
Knowledge management		0.991119			0.679104			0.817255	
Performance of startups		0.999964			0.851673				

H3: business intelligence affects the knowledge management. In examining the effects of business intelligence on knowledge management, as it can be seen in Figure 2, the path coefficient is calculated to be 0.453 and given that the T value is 5.249, so it can be concluded that such a path coefficient is significant at the error level of 0.05; that is, business intelligence has a significant effect on knowledge management, so the third hypothesis is supported and confirmed.

H4: innovation affects the performance of startups. In examining the effects of innovation on the performance of startups, as it can be seen in Figure 2, the path coefficient is calculated to be 0.828 and given that the T value is 4.127, so it can be concluded that such a path coefficient is significant at the error level of 0.05; that is, innovation has a significant effect on the performance of startups, so the fourth hypothesis is supported and confirmed.

H5: knowledge management affects the performance of startups. In examining the effects of knowledge management on the performance of startups, as it can be seen in Figure 2, the path coefficient is calculated to be 0.585 and given that the T value is 5.789, so it can be concluded that such a path coefficient is significant at the error level of 0.05; that is, knowledge management has a significant effect on the performance of startups, so the fifth hypothesis is supported and confirmed.

H6: innovation mediates the relationship between business intelligence and the performance of startups. As it can be seen in Figure 2, the path coefficient for the relationship between the two variables business intelligence and innovation is calculated to be 0.771, and it is calculated to be 0.828 for the relationship between the two variables innovation and the performance of startups. However, given the significant T Value obtained for the relationship between innovation and the performance of startups, a significant relationship can be concluded between business intelligence and the performance of startups through innovation, so the sixth hypothesis is supported and confirmed.

H7: knowledge management mediates the relationship between business intelligence and the performance of startups. As it can be seen in Figure 2, the path coefficient for the relationship between the two variables business intelligence and knowledge management is calculated to be 0.453, and it is calculated to be 0.585 for the relationship between the two variables knowledge management and the performance of startups. However, given the significant T Value obtained for the relationship between knowledge management and the performance of startups, a significant relationship can be concluded between business intelligence and performance of startups through knowledge management, so the seventh hypothesis is supported and confirmed.

Our results are in line with Saura et al. [67], who are in a review study and concluded in the impact of innovation at both forms of data-driven innovation (DDI) and user-generated data (UGD) in the performance of companies.

6. Conclusion

In startups, innovation plays a very important role because the results and successes of these types of organizations are interesting and admirable. Innovation in startups indicates the ability of startups as a living human system to flourish and learn from the constant waves of change so that change is a natural and inevitable part of organizational life, not a separate part and a threatening event. In addition, business intelligence requires the capability to adapt quickly in response to unforeseen developments and events, market opportunities, and customer needs. In such a business, processes and structures are found that facilitate speed, adaptability, and robustness, and have a coordinated and orderly system with the ability to achieve competitive performance in a completely dynamic and unpredictable environment, and obviously, this environment is not incompatible with the current functions of the organization. Therefore, such features as business intelligence and knowledge management can play an effective and significant role in achieving new innovations. Hence, this study mainly aimed to investigate the effect of business intelligence on the performance of startups with the mediating role of innovation and knowledge management. Here, we tried to answer the question of what the effect of business intelligence is on the performance of startups with the mediating role of innovation and knowledge management. To achieve this goal, a sample of the startup managers and employees was selected and surveyed. The collected data were analyzed by structural equation modeling with partial least squares approach. The results show that business intelligence, innovation, and knowledge management affect the performance of startups. Besides, business intelligence is effective on innovation and knowledge management. Innovation and knowledge management mediate the relationship between business intelligence and the performance of startups, and this result is in line with Caseiro and Coelho [28] and Abbas

and Sagsan [29]. As a result, managers of startup companies are advised to take advantage of up-to-date technologies to facilitate innovation in their production procedure. For this purpose, they can use specialized market research teams. With more careful planning, production lines are recommended to be designed and used in such a way that the organization can have the appropriate flexibility to deliver the products and services with newer features. As another proposition, some teams should be formed to analyze the reasons for the failure and even the success of the production of a particular product or project, and the results of this study should be made available to the staff of the relevant departments. It is also suggested that by giving sufficient authority to different departments, a suitable ground should be provided and supported for creative ideas and their implementation. Startup managers are also advised to be flexible in their activities so that they do not choose just a single way to achieve a specific goal, consider other ways, and employ the best method that works with better speed and quality to reach the target.

Researchers are always faced with limitations in their research, some of which show themselves even at the beginning. One of the main pillars of research is access to statistics and information. In this regard, there are problems that have made research services such as access to books, journals, statistics, and databases To not be easily possible. This problem is partly resulted from the lack or shortage of any of the above research services, and besides, the wrong culture has made to consider these cases as private, and as a result, individuals and institutions somehow refuse to transfer their findings to others. Furthermore, unwanted variables that may be the result of special projects and methods used in research often jeopardize the internal and external validity of the research in various ways. It should be noted that in behavioral science research, it is impossible to completely control or eliminate such factors. However, researchers try to anticipate, identify, and take all necessary precautions to reduce such factors.

The limitations of the research are as follows:

(1) Shortage or lack of available scientific resources and use of a very few and limited scientific resources (at least in Persian) that are directly related to the subject under study and research. For this reason, we needed to use non-Persian sources, which itself leads to other problems, such as limiting the time of using the Internet in college, translating texts into Persian correctly, and making them uniform.

(2) Lack of similar work in this field so that despite much effort, we failed to find research that directly addresses this issue.

(3) Lack of necessary budget to carry out and advance the work, while every research work in its various stages requires spending financial costs, and obviously, academic research has no exception to this issue due to the special circumstances.

(4) Lack of proper cooperation from executive departments and institutions and officials.

(5) Uncertainty about the accuracy of the answers received from the study population

(6) Uncertainty in the correct and common understanding of the respondents about the questionnaire questions

(7) Lack of familiarity and complete information about the subject by selected people in the statistical community

(8) Low cooperation of some managers and individuals in distributing and collecting questionnaires

(9) Nonreturn of some questionnaires and their disappearance, which were very time consuming to redistribute them in some areas due to the distance.

Therefore, the researchers are proposed to conduct the future studies with proper facilities including budget and scientific resources, and also, they are recommended to compare their results to the findings of similar studies conducted in countries other than Iran. Finally, the startup companies' managers are strongly recommended to take advantage of innovation and knowledge management in order to enhance performance of their businesses.

Data Availability

There are no available data for this paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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