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Investigating the impact of Business Intelligence on the Financial Performance of Companies

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ABSTRACT

The purpose of this research is to investigate the impact of business intelligence on the financial performance of companies. This is an applied research conducted through a descriptive survey using standard questionnaires. The statistical population included all the employees of the financial companies in the city of Tehran who numbered 8231, according to the statistics of this population, using Cochran's formula, a sample consisting of 367 was formed (n=367), the individual members of which were selected using simple random sampling. Validity of the questionnaire was assessed and confirmed by the academic experts. Its reliability, as measured in terms of Cronbach's alpha (0.859), was high and thus, confirmed. The obtained survey data for the test of the research hypotheses were analyzed using SEM-PLS technique. The results indicate that business intelligence has a positive and significant effect on the financial performance and financial innovation of the understudy companies. Also, the effect of financial innovation on the financial performance of companies is found to be positive and significant.

KEYWORDS: Business Intelligence, Financial performance, financial innovation

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1. Introduction

Business intelligence and analytics facilitate data collection, analysis and information distribution and are designed to support decision making. Business intelligence is defined as a learning solution for decision support, which by profiting from technology in the three areas of data collection, data analysis, and the use of analyzed data is able to create the decision makers' required information and knowledge (Popovič et al, 2019).

Business intelligence can be viewed as a series of mathematical models and analytical methods for extracting information and knowledge from existing data, which are used for complex decision-making processes. In large organizations, decisions are made on an periodic basis. Some decisions may be more or less critical or have a long-term or short-term effect and involve people and different and hierarchical roles. The decision-making ability of the knowledge workers of an organization individually and collectively is one of the critical factors on the productivity and competitive advantage of an organization (Ahmad, 2016).

Business intelligence is related to a wide range of techniques and applications, and its purpose is to improve the quality and analysis of operations. In addition, business intelligence is the process of converting data into information in a way that enables intelligent organizations to make useful and intelligent analysis of information so that they can always adapt their behavior to the changing and dynamic environment and increase their productivity by managing knowledge and using smart technologies (Calof et al, 2015).

Business intelligence makes you capable of decision making about all factors that may affect the organization or company. This solution allows the organization to monitor positive or negative changes. In theory, business intelligence systems are expected to have countless benefits for the organizations implementing them. These benefits include greater customer satisfaction, increased revenues, and increased competitive advantage. But there are few (empirical) studies on the factors influencing the internal implementation of BI and the benefits that actually accrue to organizations implementing this system (Trieu, 2017).

In a strong and dynamic and unstable competitive environment, companies must make efforts to gather information in order to improve their decisions, which can be a challenge for any business. This process can help managers to maintain fitness and active adaptability with their environment and increase the performance of their companies (Foster et al, 2015).

Today, traditional marketing methods are insufficient, because they see customers as rational decision makers and focus on product features, product benefits, and quality (Akyildiz & Argan, 2013). It is challenging for companies that lack innovation and creativity to survive and succeed in the market. The excellent performance of employees is not always enough to obtain a competitive advantage, but in it, innovative behaviors and creativity can be seen as necessary ingredients to build it. In the present era, characterized by digitization and globalization, having creativity and innovativeness is considered an important feature in employees and is becoming the main demand of production and service organizations (Lu et al, 2020).

Despite the findings of the service innovation research, Storey et al (2016) give evidence that the innovation of financial companies is not progressing. Therefore, due to the similarity of the nature of the goods offered to customers, it hinders the ability of companies to leap towards absolute innovation. Therefore, more studies are needed to produce the required knowledge in the financial innovation of companies (Bäckström et al, 2019).

In the research conducted in the field of comprehensive organizational information systems (IS), the adoption, use and evaluation of business intelligence systems and the relationship with innovation and organizational performance have grown into an active research area in this field. Considering the focus of financial companies on business intelligence and analysis and the importance of its management, this solution should be the focus area of academic information system research. However, commentators have noted that although "the potential exists for studying business intelligence solutions in general and their implications for decision-making and control, our current understanding of these developments in academic circles is very limited" (Popovič et al, 2019).

Therefore, to narrow this gap, the main question of the research is whether business intelligence has a positive and significant effect on the performance of start-ups, considering the mediating role of innovation (case study: start-ups in Mazandaran province)?

2. Theoretical framework and research background

Business intelligence is the optimal use of technology and analytical tools of information technology in order to collect data and convert it into information and refine it into the knowledge required by the business, which ultimately enables that business to make the correct management decisions. These decisions must be made carefully and intelligently and in line with the defined goals of that business. No software product alone can claim business intelligence, but a set of new functions and tools based on the databases available in each business can provide the approach to produce the decisions needed by each business. And finally, it is managers and business owners who make vital and smart decisions by having a correct picture of their business (Popovič et al, 2019).

Financial performance is the ability to achieve financial goals at the expected level or better than that. The concept of financial performance includes different perspectives (such as shareholders versus employees), time periods (such as long term versus short term) and measures (such as market share versus profit) (Storey et al, 2016).

Rashidi Chaghakhor and Rezaiyan (2022) found that business intelligence had an effect on the financial performance of private banks. Nikkhah (2020) observed that the use of business intelligence is a major element in the causal relationship between IS implementation and organizational success. Ahmadi Esfahani (2017) concluded that business intelligence capabilities have a good effect on network learning, innovation and organizational performance. In a research, Huang et al (2022) confirmed the indirect effect of business intelligence on financial performance through the mediating role of network learning in startups, and interestingly, these two factors are necessary to improve financial performance. The study by Popovič et al (2019) showed a significant progress in the impact of theoretical understanding of the role of innovative BIS processes and functions among different BIS departments on the company's productivity dimensions. Caseiro and Coelho (2019) concluded that business intelligence affects network learning, innovation and performance. The results of the research of Fink et al (2016) indicated the existence of a significant relationship between business intelligence and information technology. Acheampong and Moyaid (2016) stated that companies that have adapted their business intelligence have experienced effective competitive advantage and market dominance and have succeeded in achieving customer satisfaction by excelling in providing services. Therefore, based on the theoretical background and the model proposed by Huang et al (2022), the research conceptual model is designed as follows:

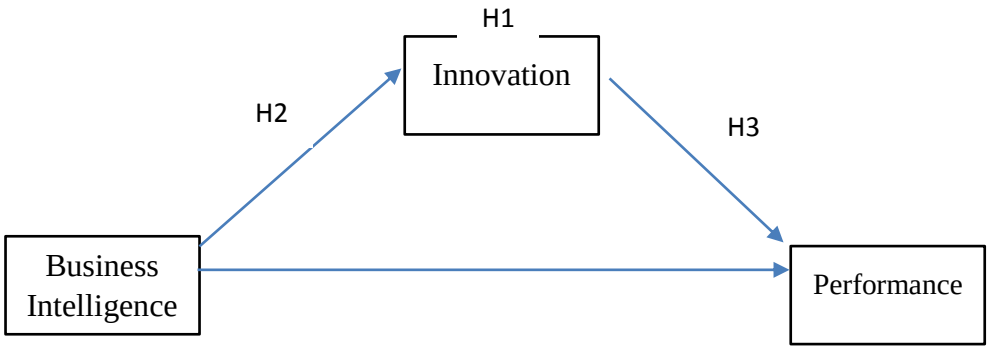

Figure1. The research conceptual model (Huang et al, 2022)

First hypothesis. Business intelligence has a positive and significant effect on financial performance of companies.
Second hypothesis. Business intelligence has a positive and significant effect on financial innovation of companies.
Third hypothesis. Financial innovation has a positive a significant effect on financial performance of companies.

3. Methodology

This is an applied research with a quantitative (comparative) approach conducted through a descriptive survey using standard questionnaires. The statistical population included all the employees of the financial companies in the city of Tehran, numbering 8231, according to the statistics. Of this population, using Cochran's formula, a sample consisting of 367 was formed (n = 367), the individual members of which were selected using simple random sampling.

For measurement of the variables, we made use of the standard questionnaire developed by Huang et al (2022) as detailed in table1.

Table1. Features of the research questionnaire

Components	Number of items
Financial innovation	6
Business Intelligence	5
Financial performance	6

The questionnaire was adapted and validated consulting the supervisor and other professors with expertise and knowledge of the field.
A preliminary test of reliability was performed by distributing the questionnaire among 30 respondents, according to which the obtained Cronbach's alpha for all variables of information sharing level and the

whole questionnaire was more than 0.7. Next, the obtained data from the whole sample was analyzed in SPSS and the SmartPLS4 software, using structural equation modeling (SEM) technique for PLS.

4. Findings

In this section, the results of confirmatory factor analysis of each research variable by SmartPLS 4 are presented. The strength of the relationship between the latent and observable variable is given by the factor loading. Factor loading is a value between zero and one. If the factor loading is less than 0.4, the relationship is considered weak and is ignored. A factor loading between 0.4 and 0.6 is acceptable, and if it is greater than 0.6, it is very desirable (Klein, 2010). The factor loadings of the research variables were calculated separately as shown in figure 2.

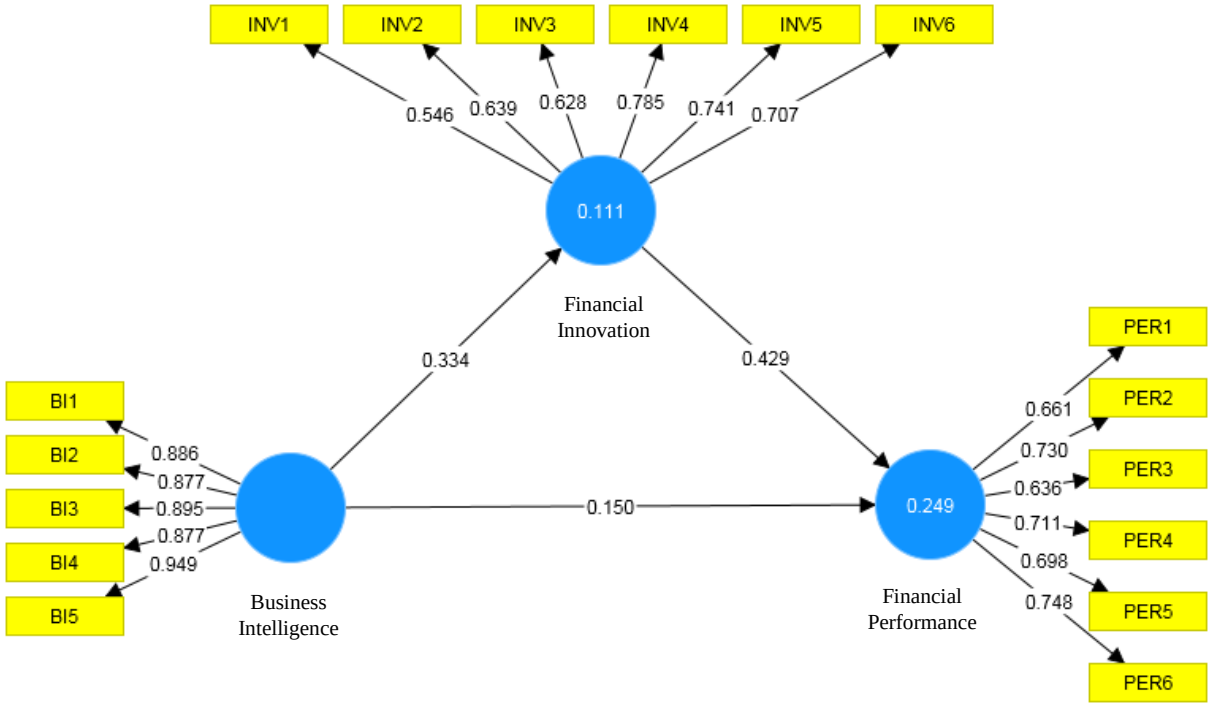

Figure 2. Factor loadings of model components in standard state

As can be seen in the figure above and table 2, in all the model's constructs, factor loadings have values greater than 0.4. Hence, the reliability of measurement models is acceptable. Having measured the factor loadings of the questions, Cronbach's alphas and composite reliability (Dillon–Goldstein's ρ) were computed, the results of which are reported in the table below.

Table 2. The results of Cronbach's alpha, composite reliability (CR), and convergent validity

Dimension	CR	Cronbach's alpha	Convergent validity (AVE)
Financial Performance	0.791	0.789	0.588
Financial Innovation	0.800	0.778	0.561
Business Intelligence	0.944	0.939	0.805

As is seen in the above table the obtained Cronbach's alpha for all dimensions is greater than the threshold of 0.7, hence the research reliability is confirmed.

To test the composite reliability (CR) of each construct, the Dillon-Goldstein coefficient (ρ) is used. The composite reliability reported in table 1 for each construct is greater than the threshold 0.7, hence composite reliability of the constructs are confirmed.

Another criterion in examining the measurement model fit in terms of internal consistency of the constructs is convergent validity which is measured by average variance extracted (AVE). In the table above, the obtained AVE for all constructs is greater than the minimum acceptable value 0.5, whereby the convergent validity of the model is confirmed.

We also use the measure heterotrait-monotrait ratio (HTMT) to assess discriminant validity. If the HTMT value is less than 0.90, there is discriminant validity among the constructs (Henseler et al, 2015).

Table 3. Discriminant validity by HTMT

HTMT	Financial Performance	Financial Innovation	Business Intelligence
Financial Performance			
Financial Innovation	0.564		
Business Intelligence	0.340	0.370	

Overall model fit

Chen (1998) proposed three values of 0.19, 0.33 and 0.67 as criterion values for weak, moderate and strong R^2 values, respectively, as the indicators of the structural model overall fit.

Table 4. R^2 values

Variable	**R^2 value**	**Adjusted R^2 value**	**Q^2**
Financial Performance	0.881	0.880	0.159
Financial Innovation	0.732	0.730	0.188

The second structural model fit index is the Q^2 index. This measure indicates the predictive power of the model regarding an endogenous construct. As a rule, Q^2 values of 0.02, 0.15 and 0.35 indicate weak, moderate and strong predictive power corresponding to an exogenous construct, respectively. Given the R^2 and Q^2 values, as reported in table 4, the structural model overall fit and predicting power is confirmed.

According to Henseler et al (2014), a standardized root mean squared residual (SRMR) value of below 0.1, and in a conservative case, of 0.08, indicates the model adequate overall fit.

Table 5. The results on the overall model fit using standardized root mean squared residual (SRMR) and NFI index

Latent variables	Saturated model	Estimated model
SRMR	0.083	0.083
NFI	0.621	0.621
d_ULS	2.012	2.012
d_G	1.321	1.321

The NFI index, which is called the Bentler-Bonnet index, is a comparative fit index. This index assesses the model by comparing the chi-square values of the independent model and the chi-square of the saturated model. An NFI value above 0.9 is acceptable, indicating the model suitability. Bootstrap provides confidence intervals for the two values discrepancy. Values greater than 0.05 for d_ULS measure (i.e. the Euclidean least square discrepancy) and d_G (i.e. the geodesic discrepancy) indicate good model fit. The obtained d_ULS and d_G values in the above table which are more than 0.05 indicate the model good fit.

By default, PLS4 software tests relationships at the 95% confidence level, and since the t-value at this interval is equal to 1.96, any relationship with a t-value outside the range of -1.96 to +1.96 is considered statistically significant at the 95% confidence interval.

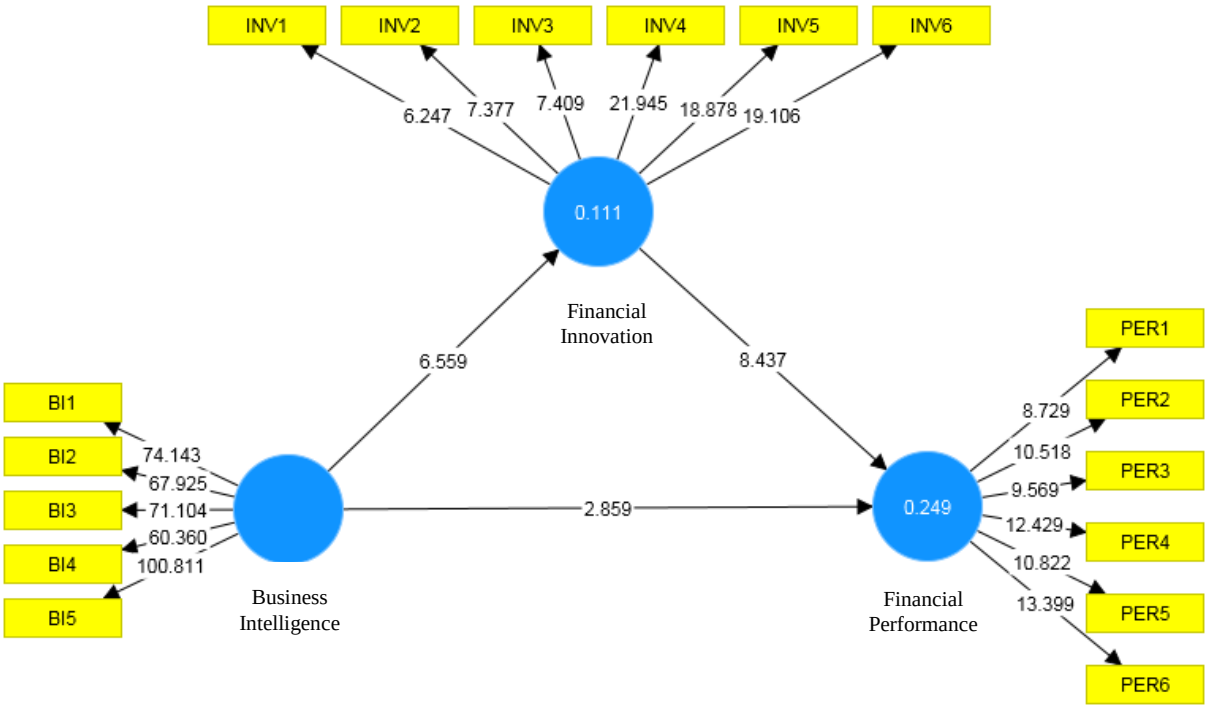

Figure 3. Significance coefficients of the conceptual model

The t-statistic shows the significance of the relationship between the variables. A t-value greater than 1.96 indicates a positive and significant effect; a t-value between -1.96 and +1.96 indicates the lack a significant effect; and a t-value smaller than -1.96 indicates a negative and significant effect. Also, if the

path coefficients are above 0.6, it means that there is a strong relationship between the two variables; If it is between 0.3 and 0.6, there is a moderate relationship, and if it is below 0.4, there is a weak relationship. As shown in the model, all the hypotheses of the model are confirmed as their t-value falls outside the specified range, indicating the significance of all hypotheses and relationships between variables at the 95% confidence interval. The results on the test of the research hypotheses are presented in the table below.

Table 6. Results on the test of the hypotheses

Path	Path coefficient	p-value	t-value	Test result
Financial innovation -> financial performance	0.429	0.000	8.437	Accepted
Business Intelligence -> Financial Performance	0.150	0.004	2.859	Accepted
Business Intelligence -> Financial Innovation	0.334	0.000	6.559	Accepted

Given the results in the above table, all the research hypotheses are confirmed.

5. Discussion and conclusion

The results of the first hypothesis testing showed that business intelligence has a positive and significant effect on financial performance. Based on prior research, we argue that business intelligence helps organizations create business value through its direct impact on business processes (Ray et al, 2005; Subramani, 2004; Tallon et al, 2000). Since business intelligence typically provides automated support for business processes and process communications (Subrami et al., 2004), examining process-level benefits not only indicates the value created, but also how value is delivered (Baroa & Mousopadia 2000; Davern & Kaufman 2000; Al-Bashir et al 2008). Business intelligence underpins financial performance, which includes improving operational efficiency (reducing cost and increasing productivity) and operational effectiveness, and developing value chain activities (Porter, 1996; Porter, 1985). Process performance benefits include supplier/business partner relationship benefits, internal process efficiency benefits, and customer intelligence benefits.

The results of the second hypothesis testing showed that business intelligence has a positive and significant effect on financial innovation. This finding is consistent with the results found by Caseiro and Coelho (2019) and Popovič et al (2019). They found positive casual relationships among different variables. From their findings, it follows that the use of business intelligence affects innovation and financial performance.

The results of the third hypothesis testing showed that financial innovation has a positive and significant effect on financial performance. The results of this research are in line with the research results of Chaslow and Baker (2015), Maritan (2007), Pavlovo and Savvy (2006) and Zahra et al. (2006) who concluded that each of the innovation processes has an impact on financial performance. It can be stated that innovation processes can be a source of dynamic capability when the opportunity is created. Financial performance is in the organization's understanding of the environment and the identification of market needs and opportunities, while organizational innovation deals with the development of new thinking in

the organization and the creation of new knowledge to augment existing resources. Coordination in financial innovation concerns allocating and equipping the organization's resources, organizing tasks and coordinating organizational activities. Finally, the integration involves the development of new organization patterns in response to internal or external competitive changes and the implementation of the appropriate configuration is achieved. Therefore, it is suggested that managers of financial companies pay more attention to its components in order to be able to appropriately implement the business intelligence system in their company. And by providing effective organizational processes in different areas, they achieve organizational understanding enabling them to better choose new business intelligence systems and optimally integrate them, and achieve better financial performance.

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ETHICAL CONSIDERATION

Authenticity of the texts, honesty and fidelity has been observed.

CONFLICT OF INTEREST

Author/s confirmed no conflict of interest.