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The Business Intelligence impact on the financial performance of start-ups

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ABSTRACT

Business Intelligence goal is to investigate, integrate and logically collect and multidimensional analysis of data from varied customer information sources, environment, competitors, markets, and etc. to enhance the performance of businesses, particularly startups. This research aims to study the impact of Business Intelligence on the financial performance of start-ups. The method is descriptive-survey, aside practical purpose. The study statistical population covered CEOs and experts of startup companies who were investigated in a 250-sample people. Also, 43-item questionnaire aside set up validity with confirmatory factor analysis, and validity analysis was employed for data collection. The results indicated that Business Intelligence did not impact Network Learning in startups, however, Business Intelligence enhanced Innovativeness in startups by 0.99, also, Innovativeness enhanced the financial performance of startups by 0.311, startups intelligence on Network Learning by 0.537, Network Learning on enhancing Innovativeness in startups by 0.632, and Network Learning on financial performance enhancement in startups by 0.397. The impact of Business Intelligence on Innovativeness as well as Network Learning confirmed, also, the impact of Innovativeness and Network Learning on financial performance confirmed. Thus, it can be concluded that the impact of Business Intelligence on financial performance has been studied indirectly through the mediating role of Innovativeness and Network Learning in startups. Surprisingly, these two factors are necessary to enhance financial performance.

Abbreviations

BI	Business Intelligence
NL	Network Learning
FP	Financial Performance
CEO	Chief Executive Officer
GOF	Goodness of Fit
AVE	Average
PLS	Partial Least Squares

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1. Introduction

A start-up is a company set in motion by an entrepreneur to explore, develop, and verify a scalable business model (Katila, Chen & Piezunka, 2012). Even though entrepreneurship assigns to new businesses, containing self-employment and businesses that never aim to become registered, start-ups assign to new businesses that aim to evolve beyond the solo founder. One of the principles of entrepreneurship is the ability to create new and useful ideas that solve human problems (Raghuvanshi, Agrawal & Ghosh, 2017). Entrepreneurs, especially when combining resources in new and different ways to gain a competitive advantage over competitors, can succeed in creating market value and improve financial and non-financial performance (Guzman & Kacperczyk, 2019). Meanwhile, the importance of Business Intelligence in today's organizations is undeniable because they enable the ability to monitor market trends and movements of competitors and customers by providing information to companies (Wanda & Stian, 2015). It is important to study the impact of the Business Intelligence on improving the learning and innovation capabilities of individuals in a start-up business that ultimately affects its financial performance.

Villar, Alegre and Pla-Barber, (2014) stated that Business Intelligence is an invaluable, and irreplaceable internal resource that helps start-up companies develop and expand their knowledge base for managers. Lasi (2013) has stated that the goal of Business Intelligence is to automate and integrate as many business steps and functions as possible. Recently, the implementation and deployment of Business Intelligence systems has become one of the main priorities of senior information managers of organizations. Business Intelligence can have a significant effect on the performance of a company and is therefore an important priority for many companies. Cutter Consortium Report (Hawking & Sellitto, 2010) survey of 142 companies found that 70 percent of respondent companies implemented data warehousing and Business Intelligence. However, Wagonfeld (O'Leary, 2011) study showed that a significant number of companies have failed to realize the expected benefits of Business Intelligence. Moss and Atre (2003) investigation showed that 60 percent of Business Intelligence projects have failed, or those that have been implemented have poor quality due to poor planning, poor project management and unmet business needs. To establish a Business Intelligence system, five steps can be considered: (a) Identifying the intelligent information required by the organization (Chen & Lin, 2021), (b) Extracting and collecting data from existing information sources (Yiu, Yeung & Cheng, 2021), (c) Concentrating and organizing data in an information warehouse such as a data warehouse (Strohmeier, 2021), (d) Provide appropriate analytical tools and display results (Nuseir, Aljumah & Alshurideh, 2021), and (e) Perform operations (Chung & Tseng, 2012). In their research, Man, Lau and Chan (2002) showed that three characteristics affect the success of start-up businesses: internal factors, individual characteristics and entrepreneurial characteristics. Using factor analysis statistical method, Caseiro and Coelho (2019b) studied the success and failure factors of entrepreneurship. The results showed that from the perspective of entrepreneurs, corporate reputation and management (including honesty and social skills), and entrepreneurial personality traits are the most important factor for success. The most important problem was the tax system and the inability to maintain reliable staff. Hani (2021) used network analysis to prioritize the factors that affect the success of start-ups. These factors included global market trade, organizational culture, experience, education, industrial relation, government support, creativity, customer relationship, and etc.

This study aims to investigate the Impact of Business Intelligence on the financial performance of Start-ups. The method is descriptive-survey, aside practical purpose. The study statistical population covered CEOs and experts of startup companies who were investigated in a 250-sample people. Also, 43-item questionnaire aside set up validity with confirmatory factor analysis, and validity analysis was employed for data collection.

2. Problem statement and methods

Startup success factors can be classified into three factors: organization, process, and technology. The organizational factor includes support for committed management, a clear vision, and a well-established business. The process factor includes business-based competition and balanced team composition, an interactive business-based development approach, and user-oriented management. The technology factor includes business-based, scalable and flexible technical framework, and the quality of data integration. Thus, startups need prerequisites to implement Business Intelligence, without which investment will not pay off.

2.1. Variation definition

Financial performance (dependent variables) shows the growth of the company in terms of sales and profitability, stock status and stock growth rate of companies, net profit margin and operating profit margin, and etc. In this study, a standard questionnaire with 10 questions in the range of five answers (from Totally agree to totally disagree) was used. The main tasks of Business Intelligence (independent variable) include exploring, integrating and intelligently accumulating and multidimensional analysis of data from various information sources. For Business Intelligence, a standard questionnaire with 15 questions was used. Network learning (mediator variable) refers to inclusive learning in the organization by relying on communication networks within different parts of the organization as well as communication networks with partners, colleagues, customers, etc. in order to keep the knowledge level of companies up to date. For network learning, a standard questionnaire with 6 questions was used. Innovativeness (mediator variable) is an important factor in creating value and helping to meet customer needs in the development of new capabilities that drive the achievement and maintenance of better performance or superior profitability in complex, competitive and rapidly changing environments. For innovativeness, a standard questionnaire with 12 questions was used.

2.2. Financial performance

After reviewing published articles (from 1996 to 2001) in management journals, Cartoon (Prugsamatz, 2010) found that out of the 138 selected articles, the dependent variables (factors) of organization performance were 70% profitability, 27% market growth, 17% market-based metrics, and 18% other performance metrics. Other factors are considered as one of the performance metrics were up to 4% of the articles. In most of the mentioned researches, the two factors of profitability and organization market growth are considered as variable factors of the organization performance. In general, the factors of the organization performance can be seen in Table 1.

2.3. Network learning

Larsson, Bengtsson, Henriksson and Sparks (1998) consider network learning to mean organizational groups that aim to learn with each other, from each other, and from the mutual relationship. Therefore, its main focus is on group dynamics and learning of individual group members instead of collective learning. Scientists in this network area do not see the learning as entity, but a platform for learning. Ali and Anwar (2021) considers network learning based on four assumptions (Table 2):

(a) Learning is not limited to individual level, but it can be used in other system levels, (b) Inter-organizational network is the fourth level of learning after individual, group, and organizational learning, (c) Network learning should be studied in networks wider than strategic networks to be evaluated for correlation with organizational learning, and (d) Network learning is the group learning of organizations in any individual, group, organizational, and inter-organizational context.

2.4. Data collection methods

In this study, the library method has been used to collect the information in the field of research literature and theoretical foundations, as well as the background of research in research-related fields. The data collection tool was a standard questionnaire whose questions were adapted in the field of research variables. Table 3 shows the characteristics of the research questionnaire. To determine the sample size (Zahra & Garvis, 2000):

$$n = \frac{\frac{z^2pq}{d^2}}{1 + \frac{1}{N}\left(\frac{z^2pq}{d^2} - 1\right)} \tag{01}$$

Where "n" is sample size, "N" is community size, "Z" is 1.96, and confidence level and error rate are $p = 50$ and $q = 50$.

2.5. Tool reliability

Reliability (the correlation between a set of scores and another set of scores in an equivalent test obtained independently on a group of subjects (Mohan, Harun, Srividya & Verma, 2010)), is a feature of the measurement tool and shows, under the same conditions, to what extent it gives the same results. Usually, the reliability factor range is from zero (no correlation) to one (full correlation). The reliability coefficient indicates to what extent, measuring tools, measures the subject's stable/ variable characteristics. It should be noted that the reliability of a test can vary from situation to situation and from group to group.

In this study, to confirm the reliability of the data collection tool, the questionnaire, Cronbach's alpha coefficient was used to measure reliability. This method is used to calculate the internal consistency of measuring instruments such as questionnaires or tests that measure different characteristics. In such tools, the answer to each question can take different numerical values. To calculate the Cronbach's alpha coefficient, first, the variance of the scores of each questionnaire questions subset, and the total variance should be calculated. Then (Christmann & Van Aelst, 2006):

$$ra = \left(j\Big/\left(j-1\right)\right) * \left(1 - \left(\sum s2j \,/\, s2\right)\right) \tag{02}$$

Table 1
Factors of the organization performance.

No.	Factor	Definition
1	Profitability	Accounting metrics and ratios that include gross income or part of net income, such as profit to sales ratio
2	Market Growth	Metrics and ratios that include some indicators of the organization's growth, such as the growth of the company's sales over a period
3	Operation	Performance metrics on the level of the organization development in non-financial areas, such as the company's market share
4	Market-based metrics	Metrics and ratios that include the market value of the organization, such as the amount of income of stockholders and Jensen's alpha
5	Sales performance	Includes metrics that link the organization performance to how the organization's resources are used, such as sales per capita in terms of employee's number
6	Market liquidity	Includes metrics for measuring an organization's ability to meet its financial arrangements on time, such as the debt-to-assets ratio
7	Market Size	Includes metrics that represent the size of the organization, such as the employees' number
8	Business survival	Metrics for measuring the continuity of the organization in the relevant industry
9	Other factors	Other metrics and mental evaluations of CEOs about the ideal organization performance

Table 2
Forms of network learning (Larsson et al., 1998).

		Do common cognitive structures change? No	Yes
Do inter-organizational activities change?	No	Inter-organizational learning individual / group / organizational	Cognitive
	Yes	Behavioral	Hybrid

Table 3
Variables, factors, and value of factors in the questionnaire.

Variable	Variable type	Number of questions	Number related to each question	Factor'svalue	Scale	Ref.
Demographic questions	—	3	1–3	Optionalization	Nominal	
Business Intelligence	Independent	15	4–18	1,2,3,4,5	Sequential	(Zahra, Neubaum & El–Hagrassey, 2002)
Innovation	Mediator	12	19–30	1,2,3,4,5	Sequential	(Souchon, Sy-Changco & Dewsnap, 2012)
Network learning	Mediator	6	31–36	1,2,3,4,5	Sequential	(Weerawardena, Mort, Salunke, Knight & Liesch, 2015)
Financial performance	Dependent	10	37–46	1,2,3,4,5	Sequential	(Narteh, 2018; Sardana, 2009)

Where "ra" is reliability factor, "j" is Number of questionnaires or test questions, "s2j" is Subtest variance of "j", "s2" is the total variance of the test. Table 4 shows the outputs of this process Eqs. (01)–((03)).

By Goodness of Fit (GOF) (Henseler & Sarstedt, 2013), the researcher can control the overall fit after fitting the measurement part and the structural part of the research model.

$$GOF = \left(\frac{\sqrt{\overline{R^2} * \overline{communalities}}}{1} \right) \tag{03}$$

Where "communalities" is average common values of each structure, and "R^2" is R-Square of model endogenous structures. The values of 0.01, 0.25, and 0.36 represent the weak, medium, and strong values for GOF.

2.6. Conceptual model development

In this study, the "Business Intelligence" (Kitsios & Kamariotou, 2021; Muntean, Dănăiaţă, Hurbean & Jude, 2021; Nithya & Kiruthika, 2021; Nuseir & Mohammed, 2021) is an independent variable. Also, "Innovation" and "Network Learning" (Gorzałczany, Rudziński & Piekoszewski, 2021; Maggi & Marrella, 2021) are mediating variables, and finally, the "Financial Performance" is a dependent variable. As can be seen in Fig. 1, the relationships between these variables have developed a conceptual model of research (Caseiro & Coelho, 2019a).

3. Results and discussion

The collected data from the questionnaire were analyzed using appropriate statistical methods (Choi, Yoon, Chung, Coh & Lee, 2020; Pustokhina et al., 2021; Ye et al., 2020). Then, the results were presented employing descriptive and inferential statistical procedures. Descriptive statistics such as percentage and frequency were employed to examine and analyze information about the general characteristics of respondents. In inferential statistics, to obtain the final model of the research and its fit, Partial-Least-Squares (PLS) method was used.

Table 4
Cronbach's alpha rate for research variables (Moslemi, Hossein Erza, Bahrololom & Dehghan Dehnavi, 2019).

Key variables	CalculatedCronbach's alpha	Acceptablealpha limit	Approval/disapprovalof reliability
The whole questionnaire with 30 elementary samples	0.950	Above 0.7	Approved
Business Intelligence	0.900	Above 0.7	Approved
Innovation	0.914	Above 0.7	Approved
Network learning	0.847	Above 0.7	Approved
Financial performance	0.912	Above 0.7	Approved

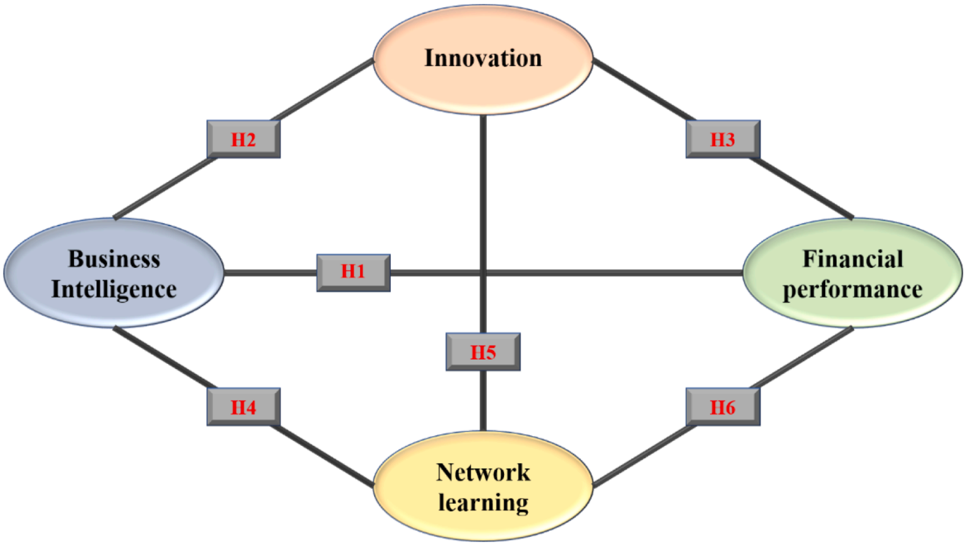

Fig. 1. Conceptual model of research (Caseiro & Coelho, 2019a).

3.1. Descriptive statistics

As can be seen in Fig. 2.a, most of the statistical sample of this research (based of education) are at the undergraduate level. Also, in Fig. 2.b, most of the statistical sample of this research (based of work experience' period) have 3 to 5 years work experience.

As can be seen in Fig. 3, most of the statistical sample of this research (based on Organizational Position) are people with the position of Chief-Executive-Officer (CEO), financial expert and marketing expert.

The results of the descriptive analysis of the research variables in the questionnaire based on Table 5 show: First, every 250 people in the statistical sample answered the research questions about the main variables. Second, considering the minimum and maximum values shows that in most questions of the questionnaire, there were all five models of " Totally disagree" to "Totally agree". In the average section, the higher the average than 3, the greater the consensus of the statistical sample of the research on that question. In the case of margin of deviation, the lower the value, the less disagreement the respondents have.

3.2. Inferential statistics

To implement statistical methods and calculate appropriate test statistics and logical inferences about research hypotheses, the most important thing is to choose the appropriate statistical method for research. For this purpose, knowledge of data distribution is a top priority. SEM was used to test the conceptual model. SEM advantage over the regression is that it can estimate all the relationships in the model together.

3.3. Evaluating validity factors of research executive model

The measurement model test includes examining the validity (discriminant validity) and reliability (internal consistency) of research structures and tools. Test reliability is related to the certainty of the measurement and its stability, so it has two varied meanings: the meaning of reliability, and stability/reliability of test scores over time. Concerning the reliability of every item, the load

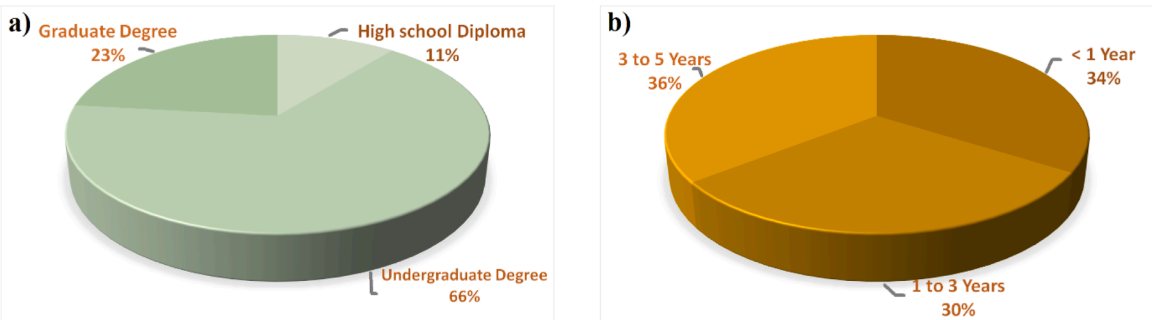

Fig. 2. Sample description based on (a) Education, and (b) Work Experience' Period.

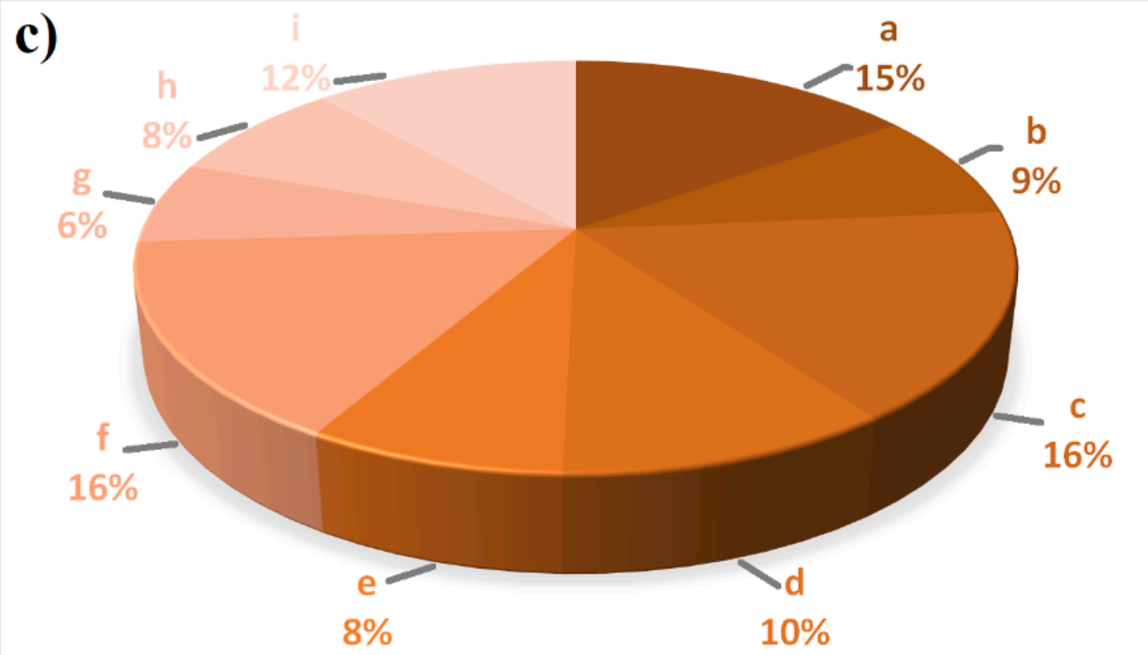

Fig. 3. Sample description based on Organizational Position (a) CEO, (b) Operational Manager, (c) Financial Expert, (d) Human Resources Expert, (e) IT Expert, (f) Marketing Expert, (g) Programming Expert, (h) R&D Expert, and (i) Technical Expert.

factor of 0.5 and more of every item is defined in the confirmatory factor analysis of a good structure indicator. Also, the load factor of the items must be significant at least at the level of 0.01. T-coefficients above +1.96 are significant at the 0.05 level. Dillon – Goldstein coefficient (cp) was used to evaluate the combined reliability of each structure. Acceptable values of the cp must be 0.7 or more. The average of the extracted variance is also important to check the reliability. AVE values should be 0.5 or higher, meaning that the structure explains at least 50% of the variance of its markers. Table 6 shows the Alpha coefficient for each of the structures, cp, and AVE.

3.4. Validity check for measuring tools

Credibility refers to whether the items measure the same concept as intended? To check the validity or discriminant validity of structures, a) The items of a structure may have the topmost load factor on their structure, and b) The second factor is that the AVE square root of a structure should be greater than the correlation of that structure with other structures. Table 7 shows the Confirmatory factor analysis for explicit variables. Also, confirmatory factor analysis for Software output and Model in meaningful state (T-value) showed in Figs. 4 and 5, respectively.

Conforming to the Table 8, entire items have the topmost load factor on their own structure and the minimum distance between the load factor connected to their own structure is more than 0.1, that reveal that the research structures have a good divergence validity. Also, Table 9 declares the outcomes of the second factor. According to the Table 9, the AVE root square of the extracted variance of all research variables is less than 0.9. Therefore, the second factor for examining the discriminant validity of research variables is established. Further, numbers below the diameter of the correlation matrix have been noted to investigate the relationship between the variables. As can be seen, the correlation coefficient of entire variables with each other is significant/positive.

3.5. Structural pattern test

Testing the structural model of the research and the research hypotheses in the PLS method is possible by examining the path coefficients (load factors) and R^2 values. Path coefficients are used to determine the contribution of each of the prediction variables in pointing out the variance of the criterion variable, and the values of R^2 indicate the variance of the criterion variable explained by the prediction variables. Further, the Stone – Giesser coefficient (Q^2) was employed to evaluate the prediction ability of dependent variables on independent variables. Positive values of this coefficient reveal the prediction ability. In Figs. 6 and 7, T-coefficients have been reported for research routes (T-coefficients less than 1.96 are not significant). Also in Table 10, estimation of path coefficients and explained variance of research variables are reported.

Table 5
Descriptive analysis of key variables (Moslemi et al., 2019).

No.	Items	Number	Minimumvalue	Maximumvalue	Average	Margin ofdeviation
1	The company's information systems are comprehensive	250	1	5	2.77	0.847
2	The company knows the wants and needs of its customers	250	1	5	2.86	0.907
3	The company recognizes the strengths and weaknesses of its product market	250	1	5	2.73	0.900
4	The company knows its large/small competitors	250	1	5	3.04	0.900
5	Information systems are well established and updated in this company	250	1	5	3.02	0.959
6	The company knows the main resources and capabilities of competitors	250	1	5	3.04	0.963
7	The company recognizes the strengths and weaknesses of competitors	250	1	5	2.91	0.910
8	The company knows the strategy of competitors	250	1	5	2.68	0.983
9	The company recognizes the bargaining power of its customers	250	1	5	3.24	0.948
10	The company is well aware of the competitive industrial environment (in which it operates)	250	1	5	2.58	1.028
11	The company examines the competitive industries trends. The managers of this company are not limited to the main operations of the company	250	1	5	2.70	1.019
12	The company's information systems are supported by the company's CEOs	250	1	5	2.41	0.945
13	In this company, reports and analyzes that cover the information needs of managers are provided regularly	250	1	5	2.34	0.977
14	The information needs of company managers are regularly reviewed	250	1	5	2.19	0.818
15	In this company, comprehensible and relatively easy reports are produced to quickly understand the industry, market and customers	250	1	5	2.23	0.883
16	The company has set realistic future goals	250	1	5	2.23	0.852
17	The company has arranged for all managers and employees to know the future vision of the company	250	2	5	4.01	0.731
18	In this company, the clarity of the future direction of the company has been instilled in the employees	250	1	5	3.97	0.733
19	The managers of this company have a realistic vision of the future of the company for all departments and employees	250	1	5	3.96	0.743
20	The company's CEOs believe that potential and balanced risks should be considered to achieve the company's goals	250	1	5	3.95	0.718
21	The company's CEOs encourage innovative strategies even if they know some of them will fail.	250	1	5	4.02	0.711
22	The managers of this company welcome big risks	250	1	5	4.05	0.734
23	The managers of this company do not like risk-taking at all (reverse question)	250	2	5	2.10	0.993
24	The company is constantly looking for new opportunities for innovation	250	1	5	3.43	0.947
25	The company has the ability to take the initiative in trying to shape its environment	250	1	5	3.45	0.927
26	The company often offers the prototype samples to its industry	250	1	5	3.50	0.924
27	The company usually takes the initiative among competitors by introducing new methods in production and service delivery	250	1	5	3.71	0.810
28	The company has established an extensive network of contacts with foreign research institutes to gain technical and non-technical knowledge	250	1	5	3.39	0.939
29	The company acquires the required technical and non-technical knowledge through attending industrial conferences and international conferences	250	1	5	3.62	0.856
30	The company combines new knowledge gained through communication networks with its existing technical or non-technical knowledge	250	1	5	3.70	0.860
31	In this company, new knowledge obtained through networks is used to solve customer problems	250	2	5	3.94	0.653
32	Knowledge gained from communication networks with other organizations is transferred to new projects through the communication network within the company	250	2	5	3.82	0.681
33	The company has turned potential and inactive resources of networked learning into productive resources	250	2	5	4.07	0.642
34	The company has grown rapidly over the past year	250	1	5	3.87	0.694
35	The company's profit margin has grown over the past year	250	1	5	3.66	0.792
36	The company has been profitable over the past year	250	1	5	3.71	0.774
37	The company's net income has increased over the past year	250	1	5	3.82	0.759
38	The company's market share has increased over the past year	250	1	5	3.82	0.763
39	The company's investment return was positive over the past year	250	1	5	3.68	0.802
40	The company was able to grow its shares over the past year	250	1	5	3.70	0.746
41	The company has been able to use its financial resources more efficiently over the past year	250	1	5	3.90	0.803
42	Customer satisfaction with the company's products or services has increased over the past year	250	1	5	3.79	0.760
43	The company's revenue growth rate has been steadily increasing since its foundation	250	1	5	3.21	0.918

Table 6
Combined reliability and average variance of the extracted research variables (Moslemi et al., 2019).

Variable / Index	cp	AVE	A
Business Intelligence	0.915	0.625	0.901
Innovation	0.933	0.544	0.919
Network learning	0.887	0.567	0.846
Financial performance	0.929	0.569	0.915

Table 7
Confirmatory factor analysis for explicit variables (Moslemi et al., 2019).

Hiddenvariable	Variable /Question	Load factor rate	Acceptable limit	Approval/disapprovalof load factor
Business Intelligence	1	0.792	Above 0.7	Approved
	2	0.775	Above 0.7	Approved
	3	0.754	Above 0.7	Approved
	4	0.704	Above 0.7	Approved
	5	0.705	Above 0.7	Approved
	6	0.777	Above 0.7	Approved
	7	0.794	Above 0.7	Approved
	8	0.806	Above 0.7	Approved
	9	0.735	Above 0.7	Approved
	10	0.761	Above 0.7	Approved
	11	0.762	Above 0.7	Approved
	12	0.782	Above 0.7	Approved
	13	0.714	Above 0.7	Approved
	14	0.762	Above 0.7	Approved
	15	0.800	Above 0.7	Approved
Innovation	16	0.727	Above 0.7	Approved
	17	0.800	Above 0.7	Approved
	18	0.723	Above 0.7	Approved
	19	0.734	Above 0.7	Approved
	20	0.760	Above 0.7	Approved
	21	0.832	Above 0.7	Approved
	22	0.826	Above 0.7	Approved
	23	0.841	Above 0.7	Approved
	24	0.766	Above 0.7	Approved
	25	0.760	Above 0.7	Approved
	26	0.721	Above 0.7	Approved
	27	0.723	Above 0.7	Approved
Network learning	28	0.783	Above 0.7	Approved
	29	0.800	Above 0.7	Approved
	30	0.804	Above 0.7	Approved
	31	0.706	Above 0.7	Approved
	32	0.799	Above 0.7	Approved
	33	0.719	Above 0.7	Approved
Financial performance	34	0.740	Above 0.7	Approved
	35	0.708	Above 0.7	Approved
	36	0.761	Above 0.7	Approved
	37	0.777	Above 0.7	Approved
	38	0.813	Above 0.7	Approved
	39	0.838	Above 0.7	Approved
	40	0.778	Above 0.7	Approved
	41	0.800	Above 0.7	Approved
	42	0.720	Above 0.7	Approved
	43	0.779	Above 0.7	Approved

3.6. Model fit and share validity

The structural model is examined and the general research model is fitted. In fact, the coefficient of determination is a more telling factor than the correlation coefficient, and it is the most important factor with which to explain the relationship between the two variables. This coefficient expresses the percentage of adjustments in the function by the independent variable. The coefficient of numerical determination is between 0 (the regression line has never been able to attribute the changes of the function variable to the independent function) and 1 (the regression line has been able to accurately attribute the changes of the dependent variable to the changes of the independent variable). Expressly, if entire adjustments in the dependent variable are explained by the regression relation, the value of the coefficient of determination will be equal to one and the other values will be between these two limits, R^2 values ~0.67, are optimal, ~0.33, are normal, and ~0.19, are weak. Q2 values are CV.Communality (evaluates the measurement model) and CV.Redundancy (evaluates the structural model and the measurement model simultaneously). Positive and large Q^2,

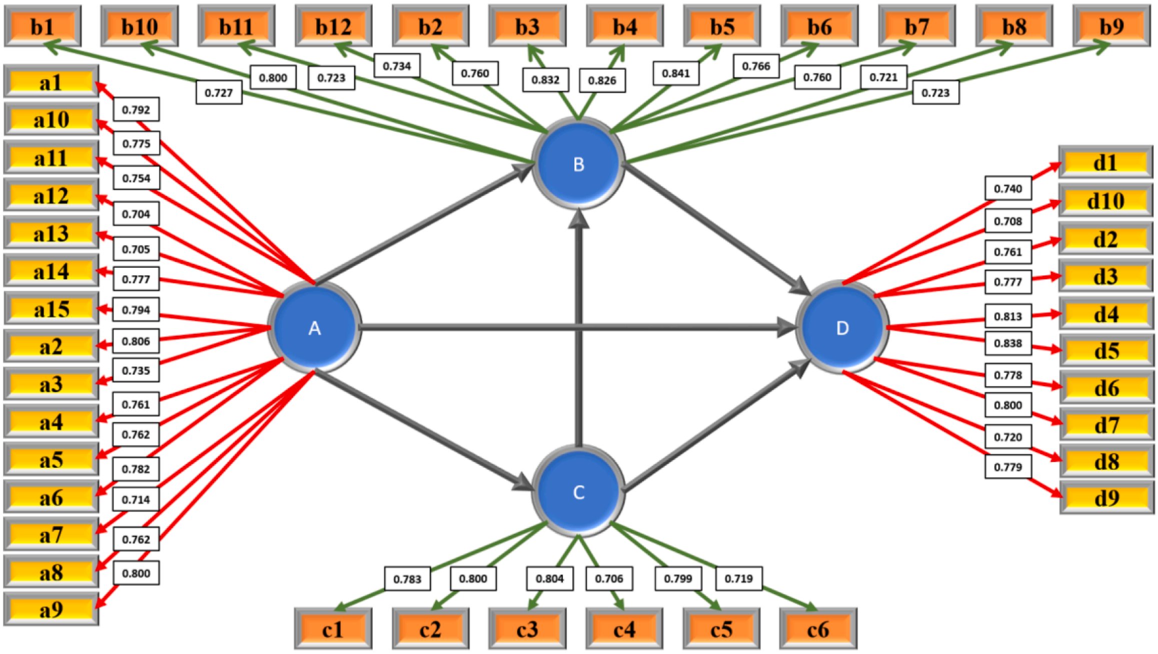

Fig. 4. Confirmatory factor analysis - Software output.

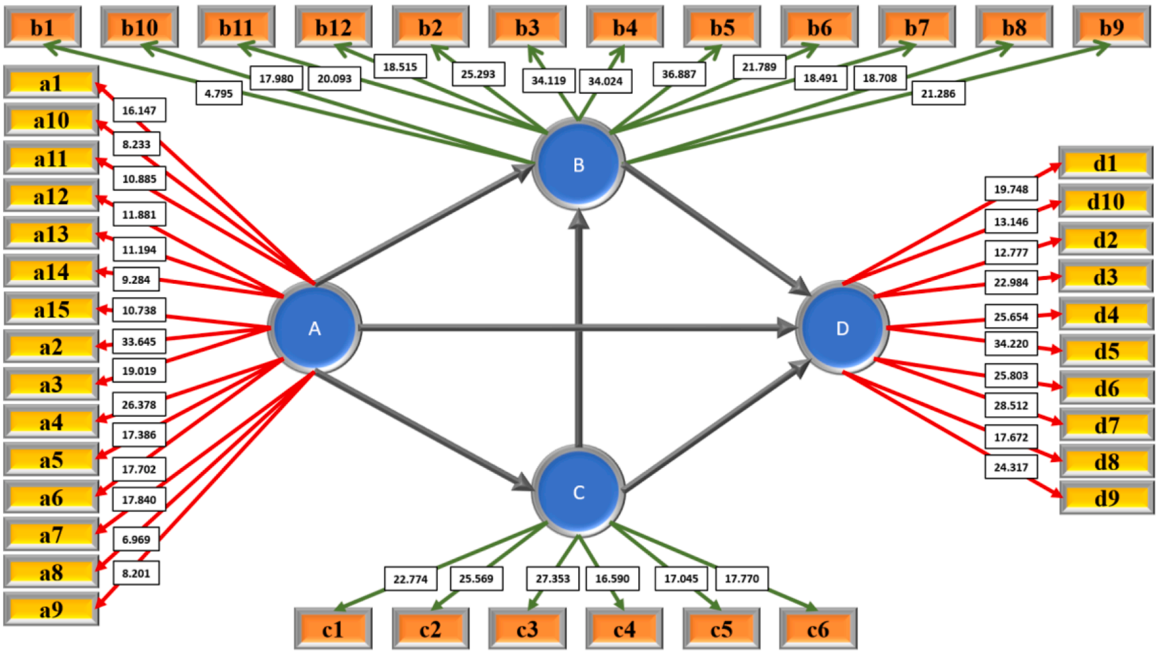

Fig. 5. Confirmatory factor analysis - Model in meaningful state (T-value).

indicates the high predictability of the model. Table 11 shows the Q^2 and R^2 values. As can be seen in Table 11, the values of the coefficients of determination indicate the degree to which the dependent variables are affected by the independent variable. In fact, from the values of the above table, it can be deduced that 0.573% of the changes in the structure of innovation, 0.288% of the changes in the structure of network learning, and 0.445% of the changes in the structure of financial performance explained by the Business Intelligence structure.

At the end, the general fit of the model is obtained, which in models based on partial least squares, the GOF index is used, which should be greater than 0.3. This index is calculated to be 0.549 for the present model, which reveals the appropriateness of the overall

Table 8
Cross-loading factors to evaluate the validity of tools in the research model (Moslemi et al., 2019).

Variable /Question	BusinessIntelligence	Innovation	Networklearning	Financialperformance
1	0.692	0.367	0.392	0.308
2	0.475	0.264	0.274	0.177
3	0.554	0.266	0.297	0.260
4	0.604	0.312	0.258	0.201
5	0.605	0.318	0.215	0.195
6	0.577	0.349	0.252	0.178
7	0.594	0.334	0.273	0.194
8	0.806	0.432	0.470	0.334
9	0.735	0.391	0.414	0.314
10	0.761	0.458	0.474	0.332
11	0.769	0.404	0.394	0.321
12	0.782	0.410	0.447	0.330
13	0.714	0.372	0.391	0.302
14	0.462	0.241	0.295	0.130
15	0.500	0.248	0.230	0.061
16	0.240	0.327	0.254	0.199
17	0.442	0.700	0.691	0.375
18	0.460	0.723	0.650	0.433
19	0.480	0.734	0.698	0.414
20	0.316	0.760	0.451	0.481
21	0.408	0.832	0.542	0.598
22	0.355	0.826	0.507	0.523
23	0.352	0.841	0.508	0.558
24	0.304	0.766	0.430	0.418
25	0.303	0.760	0.463	0.478
26	0.321	0.721	0.497	0.414
27	0.451	0.723	0.642	0.417
28	0.458	0.631	0.783	0.355
29	0.473	0.598	0.800	0.386
30	0.400	0.620	0.804	0.386
31	0.374	0.483	0.706	0.566
32	0.348	0.502	0.699	0.578
33	0.368	0.498	0.719	0.583
34	0.375	0.457	0.532	0.740
35	0.305	0.286	0.359	0.608
36	0.264	0.384	0.468	0.661
37	0.338	0.449	0.522	0.777
38	0.291	0.493	0.483	0.813
39	0.248	0.481	0.456	0.838
40	0.283	0.441	0.447	0.778
41	0.260	0.514	0.464	0.800
42	0.295	0.546	0.486	0.720
43	0.288	0.495	0.517	0.779

Table 9
Correlation matrix and root mean variance for each research variables (Moslemi et al., 2019).

Variable	BusinessIntelligence	Innovation	Networklearning	Financialperformance
Business Intelligence	–	–	–	–
Innovation	0.538	–	–	–
Network learning	0.537	0.738	–	–
Financial performance	0.391	0.610	0.632	–

model.

4. Conclusion

The Impact of Business Intelligence on the financial performance of Start-ups investigated in this study. The method was descriptive-survey, aside practical purpose. The study statistical population covered CEOs and experts of startup companies who were investigated in a 250-sample people. Also, 43-item questionnaire aside set up validity with confirmatory factor analysis, and validity analysis was employed for data collection.

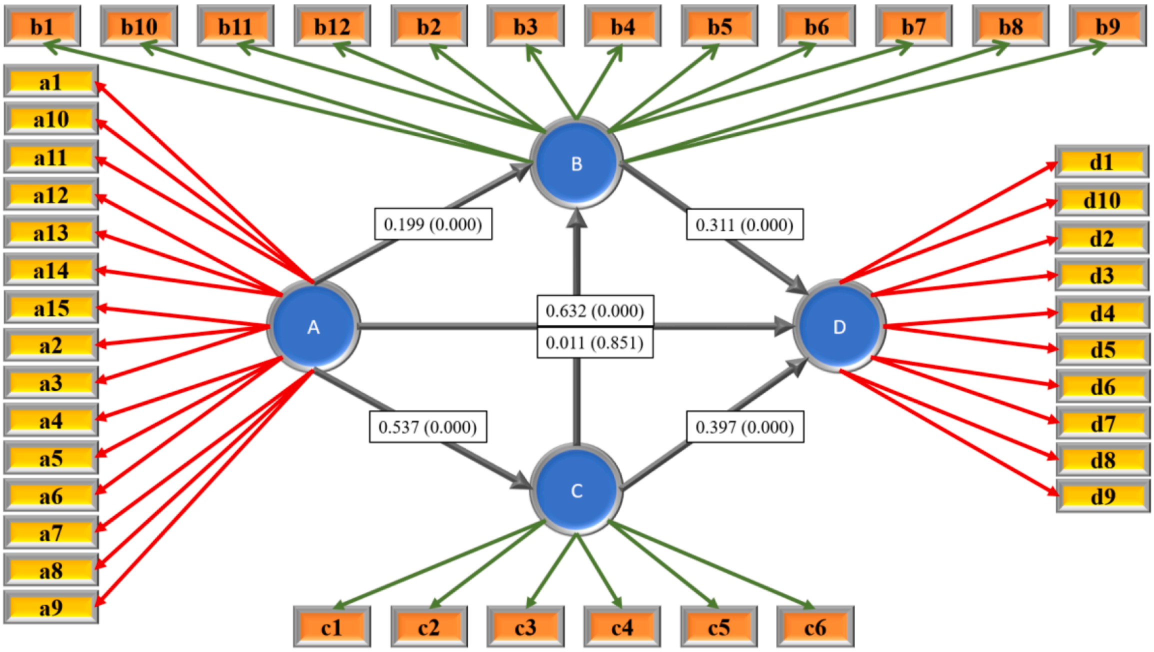

Fig. 6. Research hypotheses - Model in meaningful state (Path analysis).

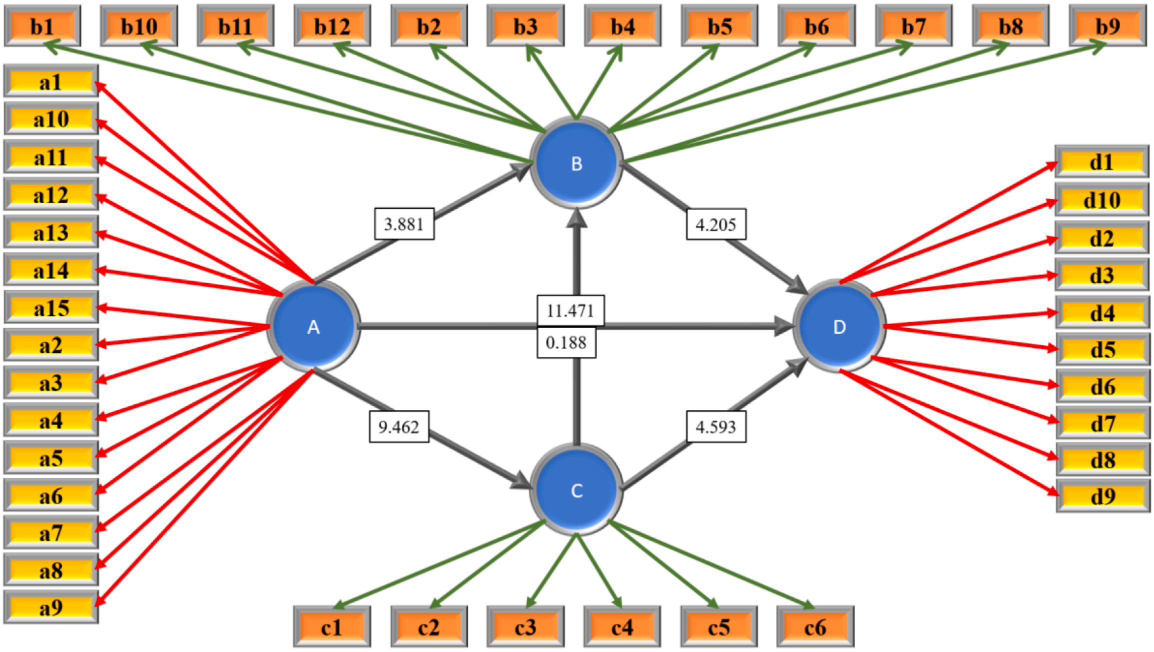

Fig. 7. Research hypotheses - Model in meaningful state (T-value).

- Because the value of the confirmatory factor analysis statistic (T-value) provided for the first hypothesis is less than 1.96, and the significance of the test is greater than 0.05, this hypothesis is not confirmed with a 95% confidence level. Thus, Business Intelligence has not affected the financial performance of start-ups.
- Because the value of the confirmatory factor analysis statistic (T-value) provided for the second hypothesis is greater than 1.96, and the significance of the test is less than 0.05, this hypothesis is not confirmed with a 95% confidence level. Thus, Business Intelligence has an impact on improving innovation of start-ups by 0.199.

Table 10
Path coefficients and T-test for the effects of variables on research hypotheses (Moslemi et al., 2019).

HypothesisNo.	HypothesisDescription	Direct pathcoefficient (B)	Tstatistics	Statistical significance	HypothesisResult
1	Business intelligence affects the financial performance of start-ups	0.011	0.188	0.851	Disapproved
2	Business intelligence has an impact on improving innovation in start-ups	0.199	3.881	0.000	Approved
3	Innovation improves the financial performance of start-ups	0.311	4.205	0.000	Approved
4	Start-up business intelligence affects network learning	0.537	9.462	0.000	Approved
5	Network learning has an impact on improving innovation in start-ups	0.632	11.471	0.000	Approved
6	Network learning has an impact on improving financial performance in start-ups	0.397	4.593	0.000	Approved

Table 11
Research model' coefficient of determination (Moslemi et al., 2019).

Structures	Coefficient of determination (R^2)	CV.Red	CV.Com
Innovation	0.573	0.524	0.601
Network learning	0.288	0.584	0.532
Financial performance	0.445	0.560	0.614

- Because the value of the confirmatory factor analysis statistic (T-value) provided for the third hypothesis is greater than 1.96, and the significance of the test is less than 0.05, this hypothesis is not confirmed with a 95% confidence level. Thus, innovativeness has an impact on financial performance of start-ups by 0.311.
- Because the value of the confirmatory factor analysis statistic (T-value) provided for the fourth hypothesis is greater than 1.96, and the significance of the test is less than 0.05, this hypothesis is not confirmed with a 95% confidence level. Thus, Business Intelligence has an impact on network learning of start-ups by 0.537.
- Because the value of the confirmatory factor analysis statistic (T-value) provided for the fifth hypothesis is greater than 1.96, and the significance of the test is less than 0.05, this hypothesis is not confirmed with a 95% confidence level. Thus, network learning has an impact on innovativeness of start-ups by 0.632.
- Because the value of the confirmatory factor analysis statistic (T-value) provided for the sixth hypothesis is greater than 1.96, and the significance of the test is less than 0.05, this hypothesis is not confirmed with a 95% confidence level. Thus, network learning has an impact on financial performance of start-ups by 0.397.

The final result of this study is that although the direct impact of Business Intelligence on the financial performance of the studied startups has not been confirmed, but because the impact of Business Intelligence on innovation and network learning has been confirmed, as well as the impact of innovation and network learning on financial performance has also been confirmed, it can be concluded that Business Intelligence has an indirect effect on financial performance with a mediating role.

CRediT authorship contribution statement

Zhi-xiong Huang: Funding acquisition, Project administration, Writing – review & editing. **K.S. Savita:** Formal analysis, Writing – review & editing, Supervision, Methodology. **Jiang Zhong-jie:** Resources, Writing – original draft, Data curation, Supervision.

Declaration of Competing Interest

There is no conflict of interests.

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