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The effect of business intelligence, organizational learning and innovation on the financial performance of innovative companies located in Science Park

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ABSTRACT

The key to business success for many companies is the correct use of data to make better, faster and flawless decisions. Companies need to use robust and efficient tools such as business intelligence (BI) as positive catalysts to achieve this goal, which can assist them in mechanizing the tasks of analysis, decision making, strategy formulation and forecasting. In other words, the purpose of using BI in these institutions is to collect, process, and analyze large volumes of data and convert them into effective business value in decision making through the creation of analytical intelligent reporting platforms. Therefore, this study aims to answer the question whether operationalization of BI, Organizational Learning (OL) and Innovation and utilization of their applications can provide financial performance enhancement for these companies. As mentioned above, the statistical population of this research is innovation companies Located in Science Park with 400 staff and according to Morgan table, 196 employees of these companies were picked as statistical case. Info accumulation tool is the questionnaire whose validity and reliability have been measured. Research findings demonstrate that BI and innovation have a critical influence on the companies conduct. But there was no meaningful relationship between OL and financial performance of these companies.

1. Introduction

The management mission and the main goal of forming any company is to make a profit and increase the wealth of shareholders (Katila, Chen & Piezunka, 2012; Lasi, 2013; Raghuvanshi, Agrawal & Ghosh, 2017). In line with this mission, it is important to pay attention to the factors that can influence the financial performance of the company because companies have limited resources and information (Villar, Alegre & Pla-Barber, 2014).

Abbreviations: CVI, Content Validity Index; CVR, Content Validity Ratio; ~~Red~~, Redundancy.

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More important than that is the success or failure and what guarantees the survival of an organization is how it works (Wanda & Stian, 2015). For this reason, there is a longstanding link between management and performance issues (DE, 2011; Moss & Atre, 2003; Strohmeier, 2021).

Among companies, innovative/startups companies, which are generally based on one idea, are weaker companies that may not survive and fail in changing political, economic, and social conditions (Man, Lau & Chan, 2002; Prugsamatz, 2010). This failure has an adverse effect on the economic sector of the society, entrepreneurship and reducing the unemployment rate (Chen & Lin, 2021; Hawking & Sellitto, 2010; Sjarif, Azmi, Yuhaniz & Wong, 2021).

Therefore, managers of these companies, in addition to paying attention to factors such as product quality, customer retention, maintaining liquidity, increasing the rate of return on investment, etc. that are necessary for sustainability in other companies, managers should pay attention to factors such as business intelligence, organizational learning, innovation and etc. Obviously, paying attention to these factors can increase the efficiency, effectiveness and durability of innovative companies (Nithya & Kiruthika, 2021; Nuseir, Aljumah & Alshurideh, 2021; Yiu, Yeung & Cheng, 2021).

According to many economic experts, entrepreneurship as an economic driver, plays a variety of roles in society and is the basis of all human developments and progress. It should be noted that not every innovation will necessarily succeed, which necessitates examining the various factors of failure (Fashanu, 2021; Hamad, Al-Aamr, Jabbar & Fakhuri, 2021; Muntean, Dănăiaţă, Hurbean & Jude, 2021).

Objectives of this paper are investigating the impression of business intelligence, organizational learning and innovation on the financial efficacy of start-up companies located in the Science Park. Main objectives are likewise: to explore the influence of business intelligence on financial efficacy of start-ups, to explore influence of organizational learning on financial efficacy of start-ups, and to explore influence of innovation on financial efficacy of start-ups. The sub-objectives of the research include: checking the significance of business intelligence on organizational learning, examining the influence of business intelligence on innovation, and examining the impact of organizational learning on innovation.

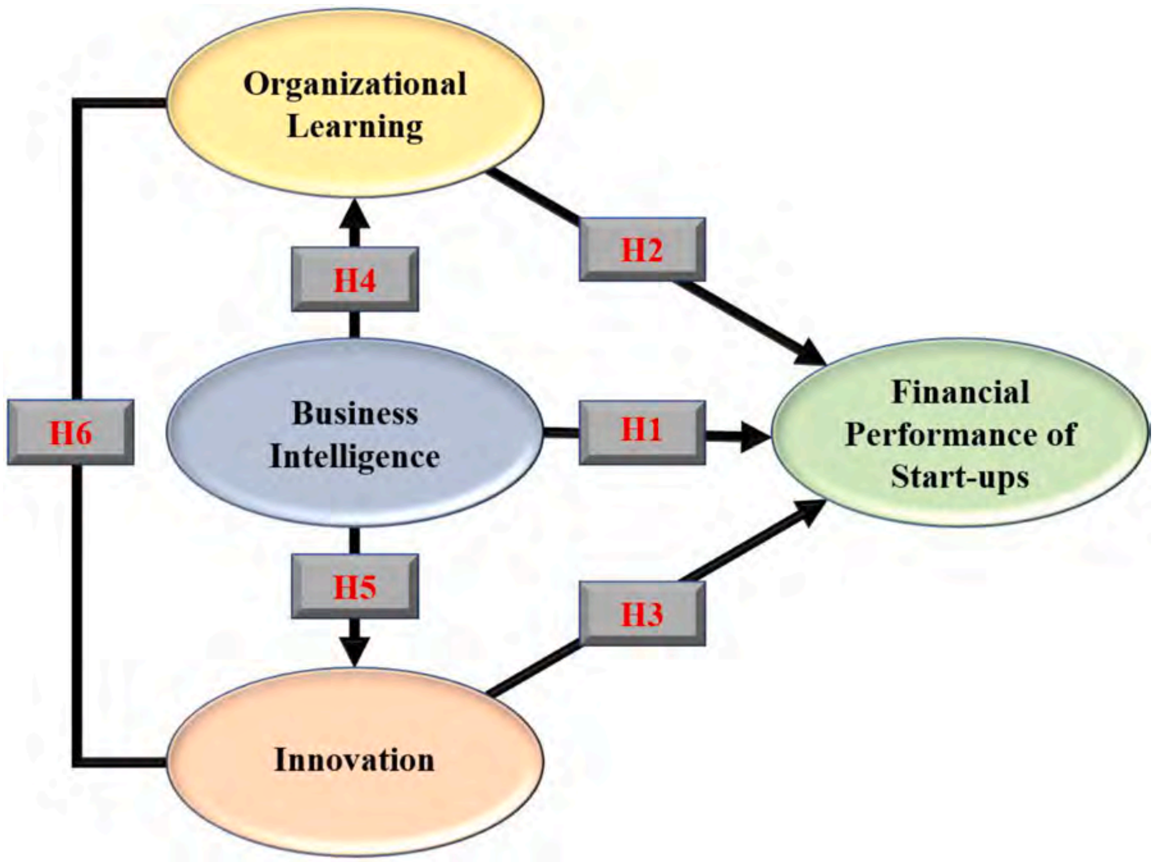

Fig. 1. Conceptual model of research (Sakhvidi et al., 2019).

2. Problem statement and methods

2.1. Research method

The research is defined as applied research in purpose, because it examines theoretical structures in scientific and real contexts and situations and seeks a solution to increase the financial performance (Cochran & Wood, 1984; Kyere & Ausloos, 2021; Waddock & Graves, 1997) of startups. Also, in terms of how to obtain scientific data, it is among the survey research, because a questionnaire tool has been used to examine each of the criteria and variables. Due to measuring the relationships between variables, the research is descriptive-correlational. It is also a field study. Fig. 1 shows the research' conceptual model (Sakhvidi, Rezaei, Shahrastani & Mahmoudi, 2019).

2.2. Statistical population of the study and sample size

Statistical population of the research is considered start-up companies located in the Science Park. The sampling of this research is simple random. Morgan table was employed to demonstrate the sample size. It was found that the number of executives of start-up companies located in the Science Park is 400 people, therefore, the required number of samples is 196 people and 280 questionnaires were distributed to ensure.

2.3. Research data collection tool

A critical phase in research is Data collection and demands the use of convenient tools. Reliable results cannot be expected from inaccurate data. Instrument design has requirements that failure to comply with, the accuracy of the data collected and ultimately distorts the research, so to design or select the instrument, it is very important to pay attention to its psychometric quality.

The present research questionnaire includes demographic information and 47 questions of research variables (Sakhvidi et al., 2019). The questionnaire was distributed online in person (according to the Corona pandemic). Attempts were made to collect information carefully and then, by analyzing them, the research hypotheses were tested.

2.4. Validity and reliability of the questionnaire

2.4.1. Validity

Due to the fact that in this study, the tool for collecting information and measuring variables is a questionnaire, validity is of particular importance. The validity of the research indicates the degree of coordination of the questionnaire with the purpose of the research. In other words, the purpose of content validity is to ensure the tools for measuring the concept that it claims to measure.

The first step is for the designers to clearly identify the target tool, it must be clear whether the tool is Predictive, Evaluative, or Discriminative. The second step is to specify the target group.

In the third step, how to select items and reduce them is considered.

To calculate the validity, two methods can be used: qualitative (expert opinion) and quantitative (calculating CVI and CVR). Content Validity Index (CVI) is a process to compute value validity measurably. CVR sizes the importance of the part that is between 1 and -1.

2.4.2. Questionnaire reliability

Reliability is one of the technical features of measuring tools. To calculate the reliability coefficient, the re-execution method, the parallel method, the composition method, and the Cronbach's alpha mode are used.

In this study, Cronbach's alpha approach was used. The approach is employed to compute the internal consistency of the measuring instrument. If the alpha coefficient is larger than 0.7, the questionnaire has agreeable reliability. Table 1 presents Cronbach's alpha. Because Cronbach's alpha of whole variables is bigger than 0.7, the case has agreeable dependability.

2.5. Research data analysis method

In the study, the demographic data of the research were described employing descriptive statistics, frequency tables and pie charts and the data were analyzed employing SPSS software. Affirmation of the relationships between factors - variables was done through

Table 1
Calculate the dependability of questionnaire.

Variable	Questionnairequestions	Number ofquestions	Cronbach's alpha
Financial performance	1 to 12	12	0.852
Business Intelligence	13 to 24	12	0.866
Innovation	25 to 36	12	0.888
Organizational Learning	37 to 47	11	0.894
The whole questionnaire	–	47	0.913

PLS modeling/confirmatory factor analysis employing Smart software that is a divergence path design method and allows the study of theory and metrics as one.

2.6. Structural equation modeling

There are two important issues in measuring variables in the behavioral and cognitive sciences. a. Measurements, and b. Cause and effect relationships between variables. Structural equation models contain 2 parts, the measurement model and the structural function model (Fig. 2). Structural Equation Models by integrating the two models of confirmatory factor analysis and structural function analysis, many problems and difficulties of measuring latent variables and inferring causal relationships between these latent variables are solved. One of the strongest and most appropriate methods of analysis is multivariate analysis, which means the analysis of different variables that in a theory-based structure, demonstrates the simultaneous influences of variables on each other. The default partial least squares method does not require the type of distribution of the measurement variables. Therefore, it is suitable and practical for data with abnormal distribution or unknown distribution.

Goodness of Fit (GOF) index is defined as:

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

3. Results and discussion

3.1. Data analysis

3.1.1. Descriptive statistics

Fig. 3 examines how statistical samples are distributed in terms of variables as age, level of education, and number of staff.

According to statistics, of the 196 sample respondents, 75 were male and 121 were female. Also, 41% were single and 59% were married.

3.1.2. Inferential statistics

3.1.2.1. The main design. In the research, structural equation design by support of Partial Least Squares pattern and Smart software has been employed to question hypotheses and accuracy of main model. The approach is employed in cases where distribution of

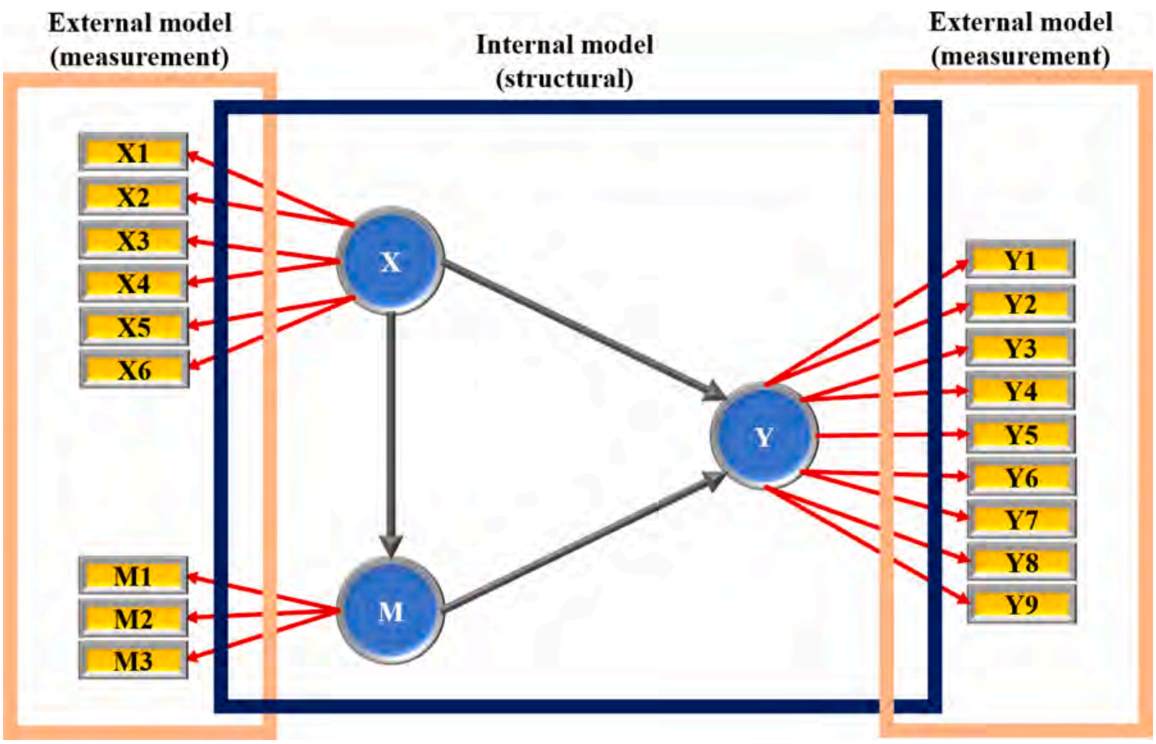

Fig. 2. Internal and external model.

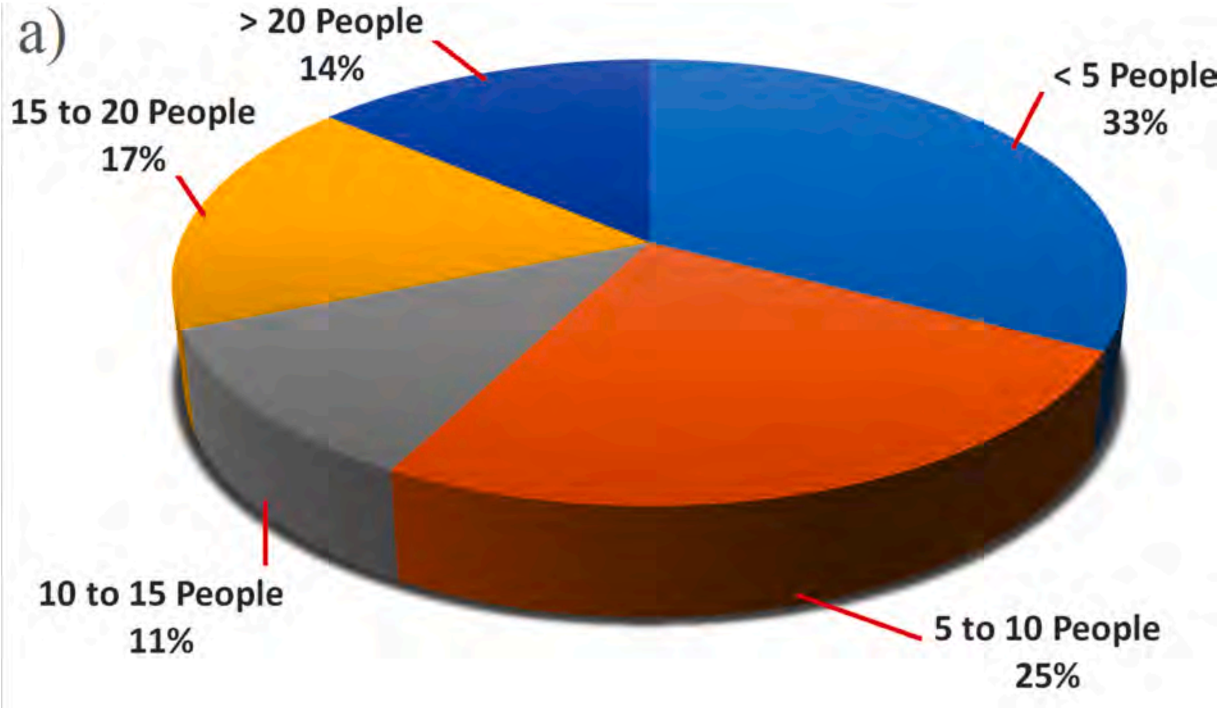

Fig. 3. Frequency distribution of respondents.

variables is not normal or the sample size is small. In PLS patterns, 2 plans are evaluated, External plan or the measurement plan and Internal plan or the structural plan in structural equation patterns. The external plan exemplifies the load factors of the observed variables.

3.1.2.2. External (measurement) model. In the fundamental equation design procedure method, it is first inevitable to study validity of the structure to demonstrate that the picked parts have the vital veracity to size their desired variables. Confirmatory Factor Analysis is employed for this aim. In such a way that load factor of every part by its variable has a rate of "t" larger than 1.96. In this case, this part has essential veracity to measure that latent variable/structure.

Tables 2 to 5 show amount of load factor for the parts of every latent variable.

The entire parts had an "t" statistic larger than 1.96, so none of the parts were detached from design. Therefore, we continue with entire items (questions) and examine the model.

3.1.3. Evaluation of external model fit

3.1.3.3. Convergent reliability and validity. In the structural equation model, aside from the construct validity, that is employed to evaluate the significance of the picked items for measuring variables, diagnostic validity is also deliberated, meaning that the items of each variable ultimately have a good separation in terms of measurement relative to other variables provide the model. In other words, each item measures only its own variable and combines them in such a way that entire variables are well disconnected from each other. The approach is determined by the extracted mean variance index (AVE). AVE coefficients demonstrate what percentage of the variance of structure or model variable is defined by a sever item. The structures or variables of the model have a larger mean variance higher than the standard index of 0.5. Therefore, it can be concluded that the items can adequately explain the variance of the research model variables.

In measurement pattern, the internal consistency of pattern or the degree of reliability is measured by calculating the composite reliability. The reliability coefficients are exhibited in Table 6. In the model, all model structures have a great composite reliability and are larger than the standard index of 0.6. Composite reliability indicates the great internal reliability of research data. Also, a Cronbach's alpha value higher than 0.7 expresses agreeable reliability.

3.1.3.4. Divergent validity. Divergent validity is measured in two ways. One is the cross-factor loading method, which compares the degree of correlation between the indices of a structure with their correlation with other structures, and the other method, which has been used in this research. The AVE square root of the latent variables in the present study, which are located in the cells placed in the main diameter of the matrix (Table 7), is greater than correlation value between them, which are arranged in the lower and left cells of

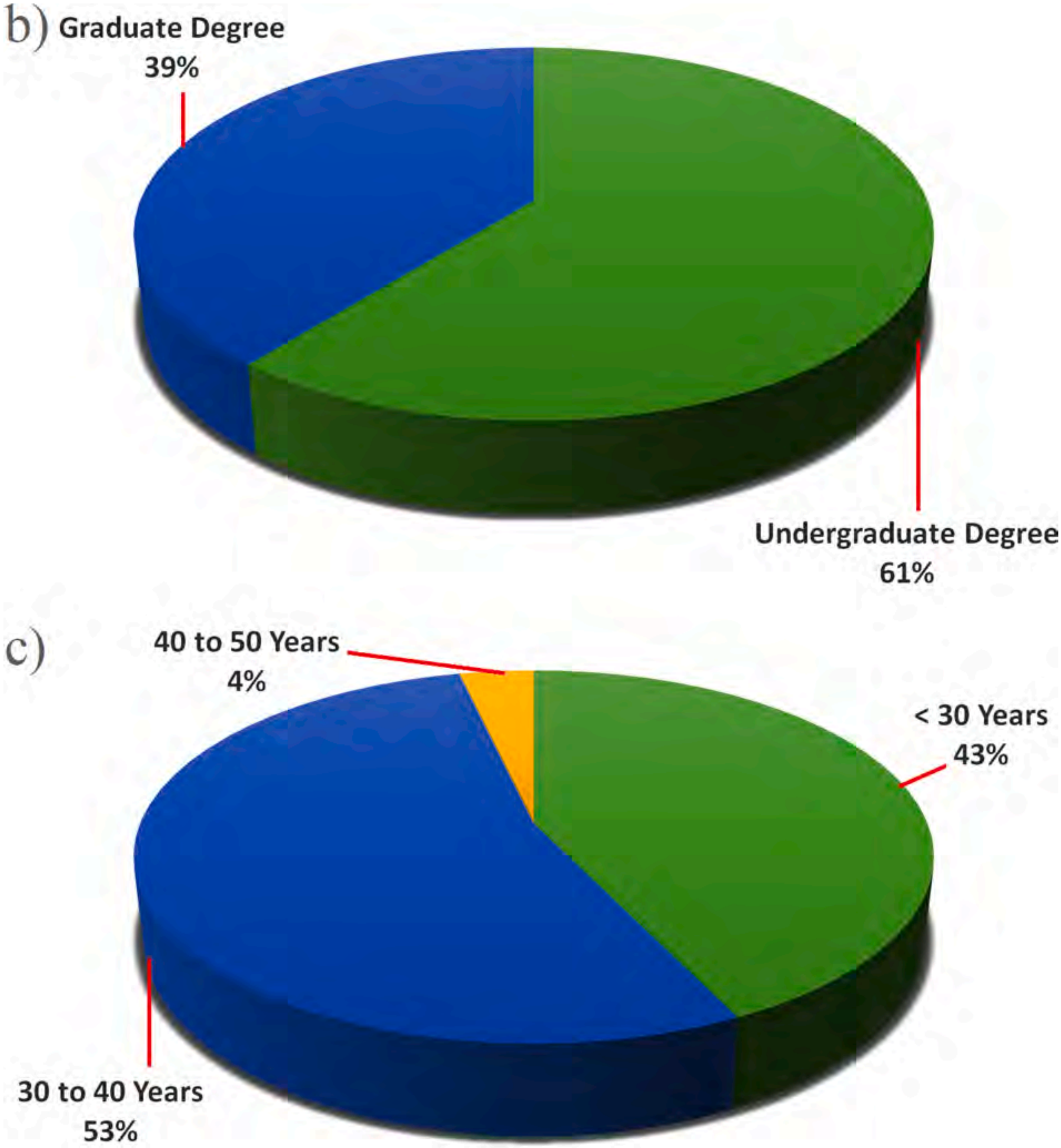

Fig. 3. (*continued*).

the main diameter. The power of this criterion was considered acceptable and confirmed the appropriate divergent validity.

3.2. Main model outputs (path coefficients and "t" statistics)

Employing the internal model, hypotheses could be inspected. By correlating the value of "t" computed for the coefficient of every path, we could confirm or reject the research hypothesis. Therefore, if certain rate of the "t" statistic is larger than 1.96, it is meaningful at the 95% trust level, and if statistical rate is larger than 2.58, the path coefficient is at the 99% trust level. In analysis, "t" statistics value for all paths except the path of organizational learning (Bilan, Hussain, Haseeb & Kot, 2020; Haseeb, Hussain, Kot, Androniceanu & Jermsittiparsert, 2019; Wiewiora, Chang & Smidt, 2020) to financial performance, is larger than 1.96 and as a result are meaningful at the 95% confidence level (Fig. 4).

Table 2
CFA (load factor and "t" rates) for Financial Performance variable (Sakhvidi et al., 2019).

Variable	Item	Load factor	Standard error	"t" statistics
FP	Q1	0.492193	0.076127	6.465460
	Q2	0.622708	0.077793	8.004666
	Q3	0.548894	0.065956	8.322162
	Q4	0.835878	0.025181	33.195080
	Q5	0.696886	0.038736	17.990588
	Q6	0.661032	0.035280	18.736782
	Q7	0.548635	0.070582	7.772977
	Q8	0.721561	0.040424	17.849916
	Q9	0.586031	0.070443	8.319190
	Q10	0.570061	0.075692	7.531324
	Q11	0.564791	0.065290	8.650437
	Q12	0.517017	0.076489	6.759327

Table 3
CFA (load factor and "t" rates) for Business Intelligence variable (Sakhvidi et al., 2019).

Variable	Item	Load factor	Standard error	"t" statistics
BI	Q13	0.730557	0.052138	14.012104
	Q14	0.589276	0.053926	10.927565
	Q15	0.597998	0.071622	8.349338
	Q16	0.732724	0.033726	21.725707
	Q17	0.733823	0.040780	17.994480
	Q18	0.770443	0.042191	18.261021
	Q19	0.616846	0.065166	9.465827
	Q20	0.475452	0.072934	6.518901
	Q21	0.559210	0.062195	8.991300
	Q22	0.615476	0.055440	11.101713
	Q23	0.673410	0.066497	10.126864
	Q24	0.517431	0.087247	5.930674

Table 4
CFA (load factor and "t" rates) for Innovation variable (Sakhvidi et al., 2019).

Variable	Item	Load factor	Standard error	"t" statistics
I	Q25	0.622802	0.054736	11.378342
	Q26	0.790376	0.031716	24.920124
	Q27	0.718456	0.036542	19.661024
	Q28	0.689335	0.046446	14.841744
	Q29	0.682036	0.047572	14.336778
	Q30	0.578895	0.065543	8.832352
	Q31	0.663431	0.044736	14.829967
	Q32	0.646462	0.050920	12.695741
	Q33	0.764198	0.034131	22.390061
	Q34	0.726147	0.047207	15.382209
	Q35	0.672393	0.049779	13.507435
	Q36	0.476731	0.062602	7.615214

Table 5
CFA (load factor and "t" rates) for Organizational Learning variable (Sakhvidi et al., 2019).

Variable	Item	Load factor	Standard error	"t" statistics
OL	Q37	0.759524	0.030754	24.696623
	Q38	0.691761	0.040261	17.181810
	Q39	0.546217	0.058348	9.361329
	Q40	0.680557	0.039109	17.401759
	Q41	0.706696	0.034220	20.651710
	Q42	0.661237	0.053347	12.395095
	Q43	0.733164	0.040780	17.978481
	Q44	0.674948	0.042602	15.843247
	Q45	0.727473	0.048557	14.981751
	Q46	0.656604	0.065271	10.059716
	Q47	0.804510	0.024279	33.136036

Table 6
AVE values and reliability indicators (Sakhvidi et al., 2019).

Variable	AVE	Composite Reliability	Cronbach's Alpha	Redundancy
BI	0.585747	0.891225	0.866388	–
FP	0.610568	0.880388	0.851707	0.152961
I	0.654413	0.907851	0.888437	0.196221
OL	0.686749	0.911863	0.893956	0.119509

Table 7
AVE values and the rate of divergence validity indices (Sakhvidi et al., 2019).

Variable	BI	FP	I	OL
BI	1.000000			
FP	0.638575	1.000000		
I	0.658450	0.667040	1.000000	
OL	0.519122	0.608079	0.750602	1.000000

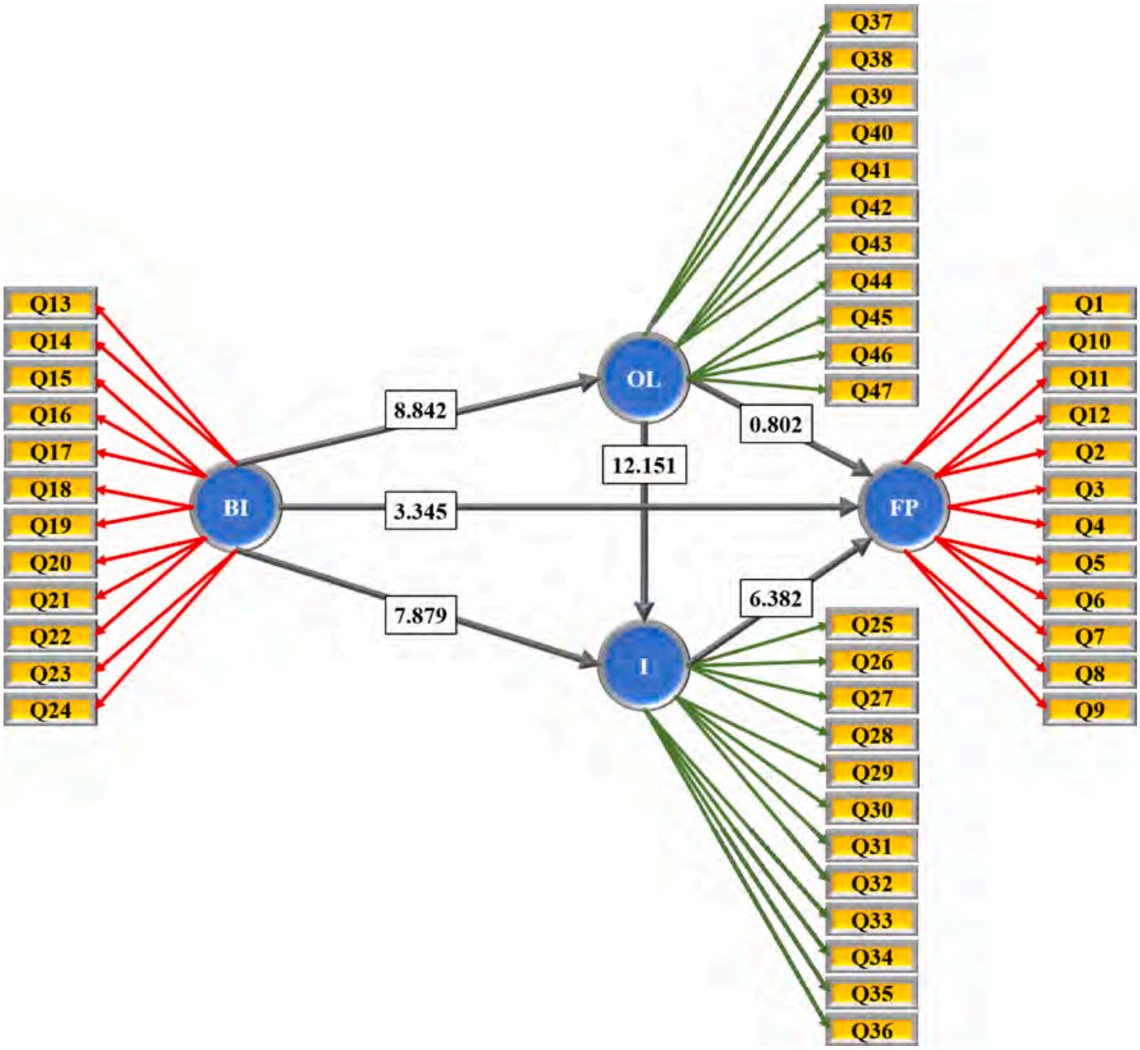

Fig. 4. The main model in the mode of critical numbers (t-value).

Numbers on routes express value of "t-value" for every path. To check the importance of path coefficients, it is decisive for "t" value of every path to be bigger than 1.96. In the assay, the value of "t" statistics for whole paths other than the path of organizational learning to financial performance, is larger than 1.96 and as a result are meaningful at the 95% trust level.

The line numbers are literally beta coefficients from the regression equation between the changeable, which is path coefficient. Circle numbers indicate the R^2 rate whose prediction changeable were entered into circle aside an arrow. The coefficient of perception for the financial performance variable is estimated to be 0.62 and shows that the variables of organizational learning, business intelligence and innovation, together, could explain 62% of the changes in financial performance. According to the value of standard coefficient and "t" statistics, variables of innovation (0.568) and business intelligence (0.233) had the topmost impact on the financial performance variable, respectively, and the organizational learning variable did not have a significant effect. (Fig. 5).

Similarly, the variables of organizational learning and business intelligence explain a total of 0.66 of the changes in innovation. According to the value of standard coefficient and "t" statistics, organizational learning variable has a greater impact on the innovation variable than the business intelligence variable. According to the number of coefficients of determination, it can be said that the business intelligence variable explains 27% of the changes in the organizational learning variable.

3.3. Internal model (structural model)

Internal pattern mode, hypotheses were investigated and structural pattern path was checked out. Every path correlate to model hypotheses. examining every hypothesis by inspecting size, sign, and statistical significance of the path coefficient (beta) between every latent/dependent changeable. The bigger the path coefficient, the larger predictor influence of latent changeable than dependent changeable. Forasmuch as outcomes of examining relationships between dependent - independent variables employing relevant coefficient, it is possible to study the influences between the research variables. To confirm the weight of the path coefficient or beta, weight of the "t-value" rate for every path coefficient should be thought-out, so the Bootstrapping approach was employed. To the aim, sampling was simulated in 500 and 800 samples. The outcomes exhibit that in both cases, there is no change in the importance or non-significance of the parameter and the outcomes have strong validity.

According to the value of "t" statistic for all paths except the organizational learning path to financial performance is larger than 1.96, which exhibits a 95% confidence level of all paths except the organizational learning path to financial performance (Table 8).

3.3.1. Evaluation of internal model fit

According to the Table 9, the effect of business intelligence on organizational learning and organizational learning pathway on strong innovation, repercussion of BI on innovation and innovation path to moderate financial performance and other paths are weak.

As can be seen in the Table 10, the predictive power of the endogenous variables of innovation and financial performance has a medium level of predictive power, which indicates a good fit for the structural model.

3.4. Evaluation of overall fit of the main model (quality indicators)

PLS-path modeling absences a general optimization criterion, i.e., there is no general function to evaluate the model fit, so in PLS-path modeling there are three different indicators for model fit: Goodness of Fit (GOF) index, Redundancy (~~Red~~) index, and Communality index.

Communality index shows how much of the variability of the indicators (questions) is explained by the related structure and the average of this index is used to determine the convergent validity (Table 11).

A suitable criterion for measuring the fit of the structural part of structural equation models is the redundancy mean value corresponding to interior structures in the model. The value is a good indicator for the fit of the structural model and is also used in calculating the overall fit of the model. The value of ~~Red~~ for the research model is 0.16, which indicates a relatively good value (Table 12).

Using the R^2 geometric mean and the mean communality index, the value of Goodness of Fit (GOF) index (Table 13), for the whole model was calculated to be 0.573, which indicates that the overall fit of the pattern is firm.

3.5. Testing research hypotheses

By inspecting and confirming the original model, the hypotheses of the research pattern have been confirmed and if certain rate of the t-statistic is fewer than 1.96, the hypothesis-zero is settled, and if the certain t-statistic value is larger than 1. 96. Assumption zero is rejected.

Hypothesis 1: Business intelligence affects organizational learning

H0: BI has no meaningful impact on organizational learning

H1: BI has a meaningful impact on organizational learning

The certain t-statistic value is 8.84 and larger than the value of 1.96, so the hypothesis-zero is rejected, i.e., at the 95% confidence level, BI has a meaningful impact on the organizational learning of start-up companies and the impact value is 0.52 and positive (direct). That is, with increasing level of business intelligence, the amount of organizational learning also increases.

Hypothesis 2: Organizational learning has an influence on innovation

H0: Organizational learning does not have a meaningful impact on innovation

H1: Organizational learning has a meaningful impact on innovation

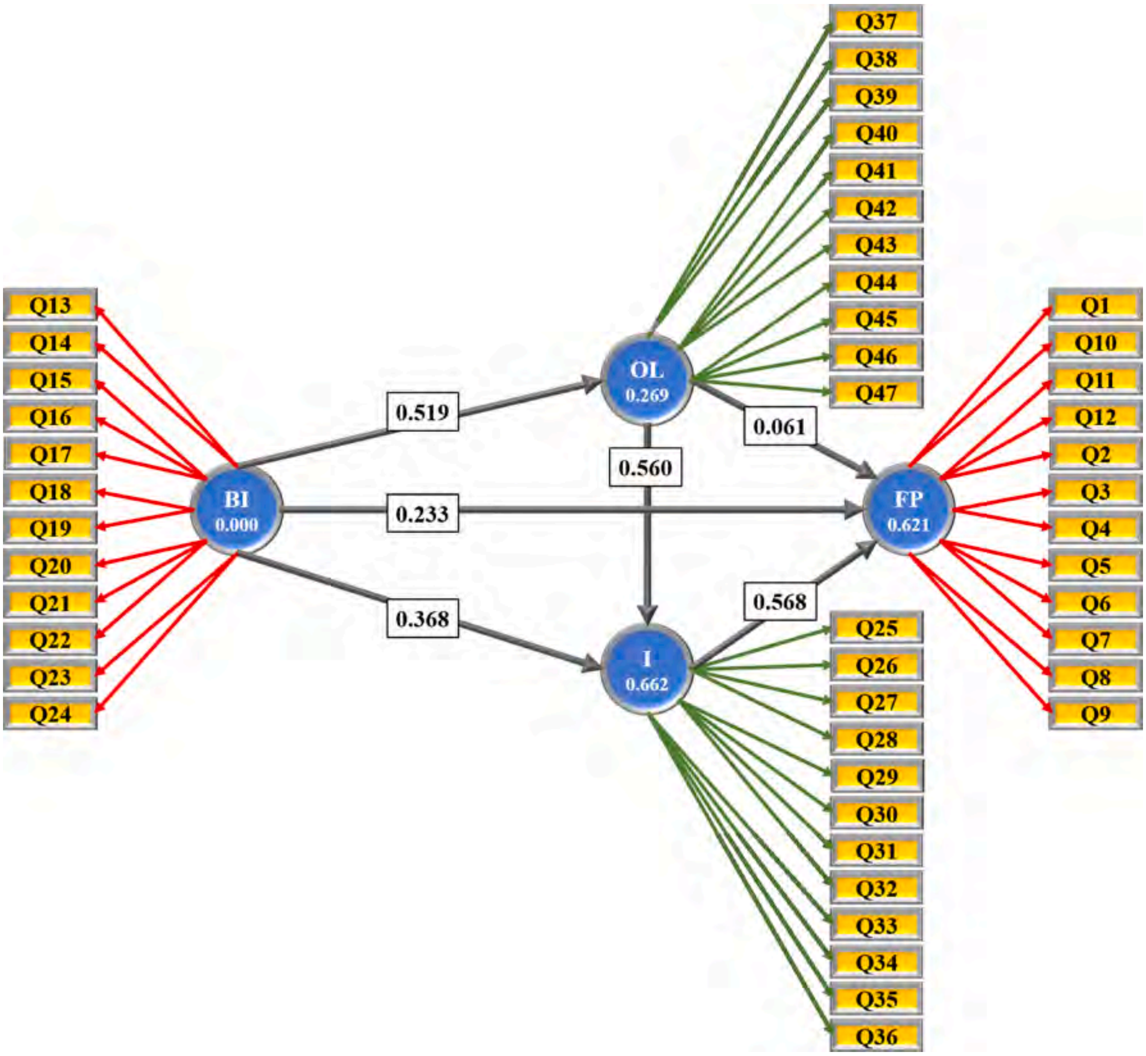

Fig. 5. The main model in the mode of path coefficients.

Table 8
Direct linear influence of role of research changeable in primary pattern (Sakhvidi et al., 2019).

Path	Beta	Standard error	t-sampling statistics		
			200	500	800
BI -> OL	0.519122	0.058709	8.842305	8.925968	9.356432
OL -> I	0.559588	0.046051	12.151371	10.658339	11.241002
BI -> I	0.367955	0.046702	7.878725	7.083970	7.421153
OL -> FP	0.060781	0.075778	0.802095	0.835589	0.841795
BI -> FP	0.233042	0.069670	3.344942	3.413065	3.370821
I -> FP	0.567971	0.088996	6.382017	6.758262	6.721716

The certain t-statistic value is 12.15 and greater than 1.96, so the hypothesis-zero is rejected, i.e., at the 95% confidence level, organizational learning has a critical influence on the innovation of start-up companies and the impact value is 0.56 and positive (direct). That is, as the level of organizational learning increases, so does the level of innovation.

Hypothesis 3: Business intelligence has an impact on innovation

H0: Business intelligence does not have a critical influence on innovation

H1: Business intelligence has a critical impact on innovation

The certain t-statistic value is 7.88 and greater than the value of 1.96, so the hypothesis-zero is rejected, i.e., at the 95% trust level, BI has a critical influence on innovation of start-up companies and the magnitude of the impact is 0.37 and positive (direct). That is, as

Table 9
Effect Size of f^2 (Sakhvidi et al., 2019).

Path	R^2_y(X excluded)	R^2_y(X included)	f^2
BI -> OL	0	0.269	0.367989
OL -> I	0.444	0.662	0.644970
BI -> I	0.566	0.662	0.284024
OL -> FP	0.621	0.621	0
BI -> FP	0.593	0.621	0.073879
I -> FP	0.514	0.621	0.282322

Table 10
Predictive Quality (Q^2) (Sakhvidi et al., 2019).

Structure	Q^2
FP	0.246701
I	0.271567
OL	0.118110

Table 11
Evaluation of quality indicators (Sakhvidi et al., 2019).

Variables	Communality index
BI	0.610568
FP	0.585747
I	0.654413
OL	0.686749

Table 12
Evaluation of quality indicators (Sakhvidi et al., 2019).

Variables	Redundancy index
FP	0.152961
I	0.196221
OL	0.119509

Table 13
Path coefficients, designation coefficients, "t" statistics and outcome of the primary pattern hypothesis (Sakhvidi et al., 2019).

Main model assumptions	Path coefficient	t-statistics	The coefficient of determination	Result
BI -> OL	0.519122	8.842305	0.269	Approved
OL -> I	0.559588	12.151371	0.662	Approved
BI -> I	0.367955	7.878725		Approved
OL -> FP	0.060781	0.802095	0.621	Disapproval
BI -> FP	0.233042	3.344942		Approved
I -> FP	0.567971	6.382017		Approved

the level of business intelligence increases, so does the level of innovation.

Hypothesis 4: Organizational learning affects the financial performance of innovative companies

H0: Organizational learning does not have a significant effect on financial performance

H1: Organizational learning has a significant effect on financial performance

The certain t-statistic value is 0.8 and less than 1.96, so the hypothesis-zero is not rejected, i.e., at 95% confidence level, organizational learning has no critical influence on the financial performance of start-up companies.

Hypothesis 5: BI impresses financial efficacy of innovative companies

H0: BI does not have a significant effect on financial performance

H1: BI has a significant impact on financial performance

The certain t-statistic value is 3.34 and greater than the value of 1.96, so the null hypothesis is rejected, i.e., at the 95% confidence level, BI has a critical influence on the financial efficacy of start-up companies and the effect value is 0.23 and positive (direct). That is, with increasing level of BI, the amount of financial efficacy also increases.

Hypothesis 6: Innovation affects the financial performance of innovative companies

H0: Innovation does not have a critical influence on financial efficacy

H1: Innovation has a critical impact on financial efficacy

The certain t-statistic value is 6.38 and greater than the value of 1.96, so the hypothesis-zero is rejected, i.e., at the 95% confidence level, innovation has a critical influence on the financial efficacy of start-up companies and the impact value is 0.57 and positive (direct). That is, as the level of innovation increases, so does financial performance.

4. Conclusion

The present study investigating the influence of business intelligence, organizational learning, and innovation on financial efficacy of innovative companies. The study is a descriptive survey in terms of method, survey in terms of purpose, applied to aim, and finally, research in terms of data collection is field research. Objectives of this paper are to answer the question whether operationalization of BI, Organizational Learning and Innovation and utilization of their applications can provide financial performance enhancement for these organizations. Also, in this research, a questionnaire that is made according to previous research and the opinion of elites has been used to collect information. The questionnaire used in this research consists of two parts. The first part includes the characteristics of people (age, gender, education, and level of work experience). The next section of the questionnaire includes questions related to financial performance, business intelligence, organizational learning, and innovation, which has 47 questions in a five-point Likert scale and was distributed among 250 staffs working in start-up companies located in the science park, finally, the sample of 196 people was achieved. In this study, descriptive and inferential methods have been used to analyze the data. Based on the analysis, out of 6 hypotheses, 5 hypotheses were confirmed and 1 hypothesis was rejected in the study population.

Results are:

- Business intelligence has a positive and critical influence on organizational learning. Particularly, improving business intelligence can improve organizational learning.
- Organizational learning has a positive and critical influence on innovation. Particularly, organizational learning can increase innovation.
- Business intelligence has a positive and critical influence on innovation. Particularly, business intelligence can increase innovation.
- Following the existence of a relationship between organizational learning on the financial performance of innovative companies, the results showed a lack of relationship between these two variables in the statistical population of the study and this hypothesis was rejected. One of the reasons is the discrepancy between organizational maturity formed in start-up companies versus large companies.
- Business intelligence has a positive and critical influence on financial efficacy. Particularly, BI can improve financial performance. This path coefficient is significant at the error level of 0.05.
- Innovation has a positive and critical influence on financial efficacy. Particularly, innovation can improve financial performance.

Despite other possible effects on "return on investment", companies with higher innovation rates are more likely to be profitable because there is innovation at work to improve business capacity to create a culture of value-added products. Better quality than competitors is critical to gaining and maintaining superior performance.

Declaration of Competing Interest

Authors declare that there is no conflict of interest respecting publication of this paper.

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