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Big Data Analytics and Now-casting: A Comprehensive Model for Eventuality of Forecasting and Predictive Policies of Policy-making Institutions

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Abstract

The ability of now-casting and eventuality is the most crucial and vital achievement of big data analytics in the area of policy-making. To recognize the trends and to render a real image of the current condition and alarming immediate indicators, the significance and the specific positions of big data in policy-making are undeniable. Moreover, the requirement for policy-making institutions to produce a structured model based on big data analytics for now-casting and eventuality of predictive policies is growing rapidly. The literature review demonstrates that a comprehensive model to assist policy-making institutions by providing all components and indicators in now-casting of predictive policies based on big data analytics is not devised yet.

The presentation of the model is the main finding of this research. This research aims to provide a comprehensive model of now-casting and eventuality of predictive policies based on big data analytics for policy-making institutions. The research findings indicate that the dimensions of the comprehensive model include: the alignment of now-casting strategies and the big data analytics' architecture, now-casting ecosystem, now-casting data resources, now-casting analytics, now-casting model and now-casting skill. The results of using the model were analyzed and the recommendations were presented.

Keywords: Big data analytics; Now-casting; Comprehensive model; Policy-making Institution.

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Introduction

Today, the world is experiencing the exponential growth of data that can be received from various resources. The pace of data growth is nearly more than Moor's Rule (Wang, Xu, Fujita, & Liu, 2016; Kapetanios & Papailias, 2018). Therefore, the term 'data' is revised and changed to 'big data' which signifies the vast outlook and evolution potentiality in different sections and areas (Elaraby, Elmogy, & Barakat, 2016). Moreover, along with the great volume of data, big data refers to the complex structure of data, its capture, and management. Big data is one of the most popular issues in areas of science and engineering that seems to embody large values. It is received in the form of the value chain and is created in a process of data discovery, data exploitation, and data integration. In the contemporary era, it has a key role in many decisions and areas of forecasting, for example business analytics, product development, health, marketing, tourism, transportation, etc. (Wang, Xu, Fujita, & Liu, 2016).

The significance of big data analytics and now-casting for policymaking organizations based on the 2013 UN Global Pulse report is undeniable, this comes as the world is witnessing a burst of data volume, variety and speed of production as the result of the emergence of new technologies and digital devices.

The UN has recognized the positive effects of big data in projects and asked for greater usage of big data to inform the deciders and to assist the achievement and success of the newly established universal purposes for sustainable development under the theme of "Evolution of Data for Development". From the UN's perspective, big data is not only popular among scholars but also very attractive in policy-making areas (Njuguna, 2017). The main difference between big data and traditional data lies in the time value and the ability to process a large volume of data in real-time that is more valuable than cases in which data has a delay (Thiemann, 2016). Consequently, data-driven decisions and usage of now-casting data-driven models concentrate on real-time to promote forecasting the use of data-driven decisions (Richards & King, 2013) in addition to providing better conditions for managers to accomplish corrective measures necessary for political purpose and investing strategies (Wang, Xu, Fujita, & Liu, 2016). What has recently grabbed attention is the integration between big data and now-casting.

Concerning the importance of big data, large quantities of explorations have been done about the achievements and challenges of big data usage during recent years (Alexander, Das, Ives, Jagadish, & Monteleoni, 2017). However, it is still experiencing great challenges, and it is too soon to claim the existence of "a standard outlook for working with big data" (Wang, Xu, Fujita, & Liu, 2016). The concern of the lack of a theory about big data growth or maturity still exists (West, 2013).

The industry of big data has challenged the traditional statistic and economy (Einav & Levin, 2013) as well as the nourishing of data for the decision making process. These challenges, on the one hand, are related to applied areas such as challenges in management and analytics of big data including challenges of capture, storing and organizing, data analytics and data visualization, semantic challenges and non-technical challenges; on the other hand, they are connected to the systematic and technical struggles due to the constant development of technology and new methods (Wang, Xu, Fujita, & Liu, 2016).

The simplest explanation in expressing the hidden problems related to big data is the existence of traditional tools, disability to confront with volume, speed and innate complexity of data (Madden, 2012) because of a structural void, (Arribas-Bel, 2013), the growing size of data and heterogeneity of collected data (Carbone, Jensen, & Sato, 2016) and also hypothesis and theories as well as testing and used models to forecast the big data (Silver, 2013).

Systematically and technically speaking, the great volume of unrestrained, extremely diverse, complex, uncategorized and unsupervised data and in combination with low volume, quantitative, classified and supervised data has created the obvious challenge for the common computational environment to process unstructured data for extraction of features or representation of data in a structured form. Consequently, the necessity of scalable saving spaces and a distributed strategy for questioning and data analytics is felt (Najafabadi et al., 2015). It should be considered that big data will not solve the problems that have been scholars and statisticians' concerns for years, such as the inference of momentary events and intervention to change a system (Carbone, Jensen, & Sato, 2016). Although it has caused statisticians, scholars and economists to develop and use proper methods (Nymand-Andersen, 2016), it still appeals to traditional statistic forums in gathering, analyzing, interpreting, visualization and organizing the data.

Meanwhile, it is noteworthy that an awareness of the limitations of traditional statistics and computing approaches in facing extremely high dimensions and uncertainty of initial and boundary conditions, lack of structure and heterogeneity of big data is essential. Analogously traditional data mining approaches and methods of data exploration acts based on a similar way to the reductionist approach of classical physics.

While unstructured data discovery needs a novel computational paradigm (Carbone, Jensen, & Sato, 2016), data specialists can rely on the data completely, accurately and precisely rather than trusting the representation of data. This is why organizations appealed to data first instead of approaches based on the hypothesis (Bean, 2017).

Regarding the basis of complex systems, science that is the comprehension of a created phenomenon by multi interrelated elements and with features of being multi-dimensions, nonlinear and heterogeneous, this science can have a great impact to create a conceptual knowledge of big data (the Third World of Karl Popper). It seems that this knowledge can provide a positive feedback in the entire properties of big data (The First World of Karl Popper). Therefore, the theoretical framework of complex system science, with its approaches and methodologies, seems to be appropriate especially for modeling different data streams, interaction of entities and their effect on each other and to create features and procedures that are proper as dependents of initial conditions of data in different time and place scales (Carbone, Jensen & Sato, 2016).

Nowadays, organizations allow the data to tell their own story and refer to the main points by uploading the data. Unnecessary and extra data are omitted and more signifying and forecasting data can be analyzed using analytical sandboxes or big data centers of excellence that own flexibility and agility in monitoring the data (Bean, 2017). Thus, the ability to control big data (Thiemann, 2016) in the process of data-driven innovations (Concurrence, 2016) will lead to great achievements in business since big data is on the threshold of maturity and its greater impact on business and industrial disorder in the next decade is expected. At the moment, the organizations are seeking a combination of the agility of big data processes and the criterion of artificial intelligence efficiencies to accelerate providing the business value (Bean, 2017).

The usage of big data analytics to discover the models and new quantitative and qualitative relations in big collections of data is considerably increasing (Scheutz & Mayer, 2016). By this approach, the policy-making institutions like Central Banks can present various outlooks for their policies utilizing new data resources, new techniques, integrity and merging of quantitative and qualitative information. Moreover, the constant and regular accessibility of intelligent and structured information is a great contribution to decision-making procedures (Nymand-Andersen, 2016).

In terms of now-casting, the definition of the term and then its function along with big data is taken into consideration. This term is composed of two words: ‘now’ and ‘casting’ as a standard activity of policy-making institutions (Tiffin, 2016). The now-casting was initially used in methodology for very short time (Zhang, Han, Sun, Guo, & Dai, 2017). It combined radar data, observation data and satellite data to describe current weather conditions accurately (Thiemann, 2016). Then it was used in different areas to forecast the present conditions proper to that area and based on momentary and real-time data (Alexander, Das, Ives, Jagadish, & Monteleoni, 2017).

Furthermore, the development of measuring technologies in all social sectors done through internet interactions and cell phone networks signifies that many industries are simultaneously involved with the issue of big data scalability (Baldacci et al., 2016). Thus, the purpose of now-casting in methodology is considered as using momentary and real-time data gathered from several methodological data resources for time and place predictions in periods shorter than several hours (Zhang, Han, Sun, Guo, & Dai, 2017) and the purpose of now-casting in economic areas is forecasting of current condition and present economic situations and its developments in a short time span (Andersson & Reijer, 2015).

Big data has a key role in now-casting due to its timely accessibility and its ability to present complementary and detailed information from different angles (Baldacci et al., 2016). Consequently, the achievement and application of big data are regarded as the key parameters in the competition since corporations use strategies to achieve and preserve the data.

Among all these corporations it seems that banks and financial institutes are closer to now-casting because of the more timely and accurate forecasting (Varian H., 2018). The atmosphere of financial services will experience great revolutions in the next years and it has to converge with the revolutions in order ti moderate its strategies, structures, policies, operations and people in an innovative, practical and constructive way (Foster, 2016).

The convergence and overlap of big data and now-casting will get more obvious when now-casting is less related to cause and effect issues (Tiffin, 2016). In this regard, targeting and investing in policy-making institutions change due to the emergence of big data and the flourishing of new related technologies. And the consequence of this revolution is the movement in harmony with now-casting and eventuality of forecasting policies based on big data analytics. However, since there is no comprehensive model of policy-making in this area to converge two concepts of now-casting and big data in policy-making institutions, the need for the researcher's perspectives in both areas are essential to recognize the indicators, to determine the dimensions and components of the model and to gain the maximum investigation of research concepts, challenges and opportunities. Therefore, it seems necessary to design a comprehensive model for now-casting in policy-making institutions to enable them to improve the effect and efficiency of expenses and to achieve forecasting purposes and to guarantee the transformation of methods, models and tools from traditional to the new ones.

The main purpose of this research is to recognize the basic dimensions, components, and indicators of the comprehensive model in policy-making institutions and then designing and presenting the model. This article presents a designed comprehensive model and discusses the situation of each dimension and mentioned component in the banking sector and banking service providers. The scientific contribution of this research that provide the first comprehensive model of now-casting of predictive policies of policy-making institutions based on big data is to identify new domains of innovative and technological activities in areas of policy-making and IT, to recognize the necessary skills and expertise of policy-making institutions and to assist the chief managers to make optimal decisions about investing in area of the IT and to revise activities that are related to information technology in policy-making institutions and to correct methods, and prepared strategies to provide opportunities of gaining competitive advantage.

Literature Review

To gain a hybrid area of policy-making in big data-based now-casting, the literature is investigated from different aspects concerning big data and now-casting. The main issues with big data are indicated in Table 1.

Table 1. The Main Issues in Relation to Big Data

Issue	Researcher
Big Data Definitions and Concepts	Kapetanios & Papailias (2018), Njuguna (2017), Bean (2017), Sicular (2016), Thiemann (2016), Wang, Xu, Fujita, & Liu (2016), Kapetanios, Marcellino, & Papailias (2016), MongoDB (2016), Scheutz & Mayer (2016), Mauro, Greco, & Grimaldi (2016), Flood, Jagadish, & Raschid (2016), IBM (2016), Stucke (2016), Elaraby, Elmogy, & Barakat (2016), Najafabadi et al. (2015), (Shi, 2014), Hassani, Saporta, & Silva (2014), Levkovitz (2014), Varian H. R. (2014), Kraska (2013), Hilbert (2013), Press (2013), Gobble (2013), Cukier (2010), Manyika et al. (2012), Dumbill (2012), Jacobs (2009), Laney (2001)
Big Data Attributes	Kapetanios & Papailias (2018), Kim et at. (2016), Carbone, Jensen, & Sato (2016), Wang, Xu, Fujita, & Liu (2016), Flood, Jagadish, & Raschid (2016), Carbone, Jensen, & Sato (2016), O'Hara (2015), Varian H. R. (2014), Wu, Zhu, & Wu (2014), Dong & Srivastav (2013), Halevy, Rajaraman, & Ordille (2006), Laney (2001)
Types of Big Data	Njuguna (2017), Kapetanios, Marcellino, & Papailias (2016), Doornik & Hendry (2015)
Types of Data Items in Big Data	Kliesen & McCracken (2016), Andersson & Reijer (2015), Levkovitz (2014)
Challenges and Reasons of Big Data Failure	Njuguna (2017), Wang, Xu, Fujita, & Liu (2016), Carbone, Jensen, & Sato (2016), Elaraby, Elmogy, & Barakat (2016), Sicular (2016), Concurrence (2016), Najafabadi et al. (2015), Assunção, Calheiros, Bianchi, Netto, & Buyya (2015), Levkovitz (2014), Jagadish et al. (2014), Simonson (2014), Letouzé (2014), Taylor, Cowls, Schroeder, & Meyer (2014), Hilbert (2013)
Big Data Challenges in Policy-making Institutions	Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Foster (2016), Wang, Xu, Fujita, & Liu (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Simonson (2014)

The main issues concerning now-casting are presented in

Table **2**.

Table 2. The Main Issues Concerning Now-casting

Issue	Researcher
Now-casting Definitions and Concepts	Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Zhang, Han, Sun, Guo, & Dai (2017), Chernis & Sekkel (2017), Stucke (2016), Andersson & Reijer (2015), (Levkovitz, 2014), Banbura, Giannone, Modugno, & Reichlin (2013)
Now-casting Models	Chernis & Sekkel (2017), Bragolia & Modugno (2017), Duarte, Rodrigues, & Rua (2017), Jansen, Jinb, & Winter (2016), Kapetanios, Marcellino, & Papailias (2016), Andersson & Reijer (2015), Giannone, Lenza, & Primiceri (2015), Carriero, Clark, & Marcellino (2012a), Marcellino & Schumacher (2010), Clements & Galvão (2008), Ghysels, Sinko, & Valkanov (2007), Ghysels, Santa-Clara, & Valkanov (2006a), Ghysels, Santa-Clara, & Valkanov (2004)

The main issues with the convergence of big data and now-casting are rendered in **Table 3**.

Table 3. The Main Issues Concerning Convergence of Big Data and Now-casting

Issue	Researcher
Challenges of Big Data-based Now-casting and Reasons for Big Data Analytics Failure	Sicular (2016), Hassani & Silva (2015), Bańbura & Modugno (2014), Varian H. R. (2014), Shi (2014), Einav & Levin (2013), Rey & Wells (2013), Marz & Warren (2013), Jadhav (2013), Lohr (2013), Needham (2013), Arribas-Bel (2013), Silver (2013), Efron (2010)
Challenges of Policy-making Institution in Big Data-based Now-casting	Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Kapetanios, Marcellino, & Papailias (2016), Burdick, Fagin, Kolaitis, Popa, & Tan (2015), Fan, Han, & Liu (2014), Hunter (2014), Dhar (2013), Dong & Srivastav (2013), Domingos (2012), Osborne (2012), Donoho & Stodden (2006), Halevy, Rajaraman, & Ordille (2006), Sala-i-Martin (1997)
Now-casting Strategies of Policy-making Institution Modeling of big data	Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Bean (2017), Kliesen & McCracken (2016), Chudik, Kapetanios, & Hashem Pesaran (2016), Kim et al. (2016), Baldacci et al. (2016), Scheutz & Mayer (2016), Nymand-Andersen (2016), Tiffin (2016), Hoog (2016), Elaraby, Elmogy, & Barakat (2016), Shi (2014), Lahiri, Monokroussos, & Zhao (2015), Higgins (2014)
Researches and Articles on Big Data-based Now-casting	Koturwar & Merchant (2018), Duarte, Rodrigues, & Rua (2017), Galeshchuk & Mukherjee (2017), Federal Reserved Bank (2017), Bragolia & Modugno (2017), Chernis & Sekkel (2017), Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Hindrayanto, JanKoopman, & Winter (2016), Tiffin (2016), Galeshchuk S. (2016), Alvarez & Perez-Quiros (2016), Li (2016), Tuhkuri (2014), Galbraith & Tkacz (2016), Wong, Shi, Yeung, & Woo (2016), Elaraby, Elmogy, & Barakat (2016), Hoog (2016), Srinivasan (2016), Das (2016), Butaru et al. (2016), Kapetanios, Marcellino, & Papailias (2016), Strobach & Bel (2015), Strobach & Bel (2016), McQuade & Monteleon (2015), McQuade & Monteleoni (2016), Flood, Jagadish, & Raschid (2016), Wu & Brynjolfsson (2015), Dixon, Klabjan, & Bang (2015), LeCun, Bengio, & Hinton (2015), Box, Jenkins, Reinsel, & Ljung (2015), DelSole et al. (2015), Kuhn & Mansour (2014), Tuhkuri (2014), Kroft & Pope (2014), Mellander, Lobo, Stoarick , & Matheson (2015), (Bańbura, Giannone, & Lenza (2014-2015), Moritz & Zimmermann (2014), Lahiri & Monokroussos (2013), Koop (2013), Ouysse (2013), Banerjee, Marcellino, & Masten (2014), Gupta, Kabundi, Miller, & Uwilingiye (2013), Osadchy, LeCun, & Miller (2013), Takeuchi & Lee (2013), Dunis, Laws, & Sermpinis (2011), Merton et al. (2013), Godbout & Lombardi (2012), Choi & Varian (2012), Doz, Giannone, & Reichlin (2012), Giovanelli (2012), Dunis, Laws, & Sermpinis (2011), Monteleoni, Schmidt, Saroha, & Asplund (2011), Soto, Frias-Martinez, Virseda, & Frias-

Issue	Researcher
	Martinez (2011), Thinyane & Millin (2011), Carriero, Kapetanios, & Marcellino (2011), Elmer (2011), Goel, Hofman, Lahaie, Pennock, & Watts (2010), Figueiredo (2010), Bordoloi, Biswas, Singh, Manna, & Saggar (2010), Bańbura, Giannone, & Reichli (2010), Huck (2009), Huck (2010), Askitas & Zimmermann (2009), Ginsberg et al. (2009), Kapetanios & Marcellino (2009), Lee, Largman, Pham, & Ng (2009), Atsalakis & Valavanis (2009), Stevenson (2008), Mol, Giannone, & Reichlin (2008), Hinton & Salakhutdinov (2006), Bernanke, Boivin, & Eliasz (2005), Forni, Hallin, Lippi, & Reichlin (2005), Kuhn & Skuterud (2004), Sukittanon, Surendran, Platt, & Burges (2004), Diebold (2003), Camacho & Sancho (2003), Perlich, Provost, & Simonoff (2003)

The items presented in the above tables refer merely to indicators that are significant in making decisions and policies of big data-based now-casting analytics. Literature review signifying some frameworks, solutions, implementation steps and strategies referring directly to the issue are presented in **Table 4**.

Table 4. The Main Frameworks, Solutions, Implementation Steps and Strategies Concerning Convergence of Big Data and Now-casting

No.	Framework / Solution / Strategy/ Implementation Steps	Researcher
1	Big Data Life Cycle and Challenges	Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Flood, Jagadish, & Raschid (2016), Jagadish et al. (2014)
2	Big Data Analytics	Kapetanios & Papailias (2018), Baldacci et al. (2016), Kapetanios, Marcellino, & Papailias (2016)
3	Conceptual Framework	Kim et al. (2016)
4	NIST Big Data Interoperability Framework	Carbone, Jensen, & Sato (2016)
5	Solution Path	Sicular (2016)
6	Big Data Strategy	Big Data Framework (2018), BLOG (2017)

According to the above table, the points are presented as follows:

1. The big data's life cycle emphasizes 5 stages based on supervisory data including achievement of data, refinement of data, integration, and representation of data, modeling, and analytics of sharing and transparency of the data.
2. Executive steps in data analytics emphasize two steps. General steps consist of the preparation of big data and designing the strategy of big data modeling (Baldacci et al., 2016). Nominal steps including the initial evaluation of the potential advantages of big data for a specific indicator, determining necessary resources, analyzing big data features in terms of volume, variety and type, evaluating biases, choosing now-casting technique of big data and evaluating contribution of big data in now-casting of the specific indicator (Kapetanios, Marcellino, & Papailias, 2016).
3. The conceptual framework from the extraction of first data and pre-process to selection and integration of the final model to approach the competitions of forecasting modeling is indicated which includes two main parts of feature engineering and heuristic analytics.
4. The interactive NIST Big Data Interoperability Framework by General Big Data Working Group based on reference architecture of big data with 5 basic components including

system orchestrator, data provider, big data application of big data and designing the strategy of big data modeling is presented by Kapetanios, Marcellino, & Papailias (2016) and Baldacci et al. (2016).

5. The solution path signifies a step by step path in the implementation of data analytics that refers to Gartner researches which embody becoming a data-driven organization. This six-step path include: ‘awareness and cognition’: defining the meaning of big data analytics for organization; ‘programming’: selecting and prioritizing of Use Cases of big data analytics; ‘experiments’: justification and confirmation of big data analytics innovation; ‘stabilization and sustainability’: stabilizing the infrastructure for access and data analytics; ‘development’: establishing logical data warehouse; and ‘transformation and transfer’: empowering a data-driven organization.
6. Steps of producing a successful strategy in big data (Blog, 2017) encompass 7 implementation steps: determining the specific items by SMART[1] methodology, leveraging of a stable strategy (by methods of performance management, data discovery, social analysis, decision making science, and structural evolutions), talent discovery, temptation beyond customer’s satisfaction, guarantee of functionality and agility. For preparing a big data strategy, it is necessary to determine business objectives, evaluate current conditions, determine and prioritize use cases, prepare the plan of the big data path, and set and embed through evolution management (Big Data Framework, 2018).

The main concentration of the frameworks is on technical issues (Godfried, 2018). It compares the best ones based on the storage space of data, data capture, data analytics, searching, and division of data, visualization of data, inquiry possibilities, updating methods, transmission, and security of data (Bhatt & Chopade, 2018). These frameworks only function in stream/ real-time processing while others operate for batch processing (Mayo, 2016).

None of the implementation steps, frameworks, and strategies of Table 4 command perfection and comprehensiveness in this area and are not able to assist the policy-making institutions for big data-based now-casting with consideration of all indicators. However, the designed comprehensive model owns this feature and provides necessary guidance for policy-making in this hybrid field.

Research Model

The literature review indicates that the methods and strengths or weak points in articles and researches, due to their entities and functions, emphasize one or several specific indicators and the result of their implementations. Therefore, the lack of a specific model in this area has caused the necessity of providing and presenting a model to answer the raised hypotheses in this field. In

1. Specific, Measurable, Attainable, Relevant, Time-based

none of the articles, the direct reference to 6 dimensions of the comprehensive model, indicating in this article, is witnessed and in each research, only implicit references to some indicators are observed. As a result, the basis of the present model, regardless of the field or specific industry, is derived from all aspects of the mentioned frameworks, implementation steps, and functional researches. Figure 1 illustrates dimensions of a comprehensive now-casting and eventuality model of predictive and forecasting policies of policy-making institutions based on big data analytics; BANC[2] model and

Figure **2** signifies basic components of each dimension.

2 Big Data Analytics and Now-casting Comprehensive Model

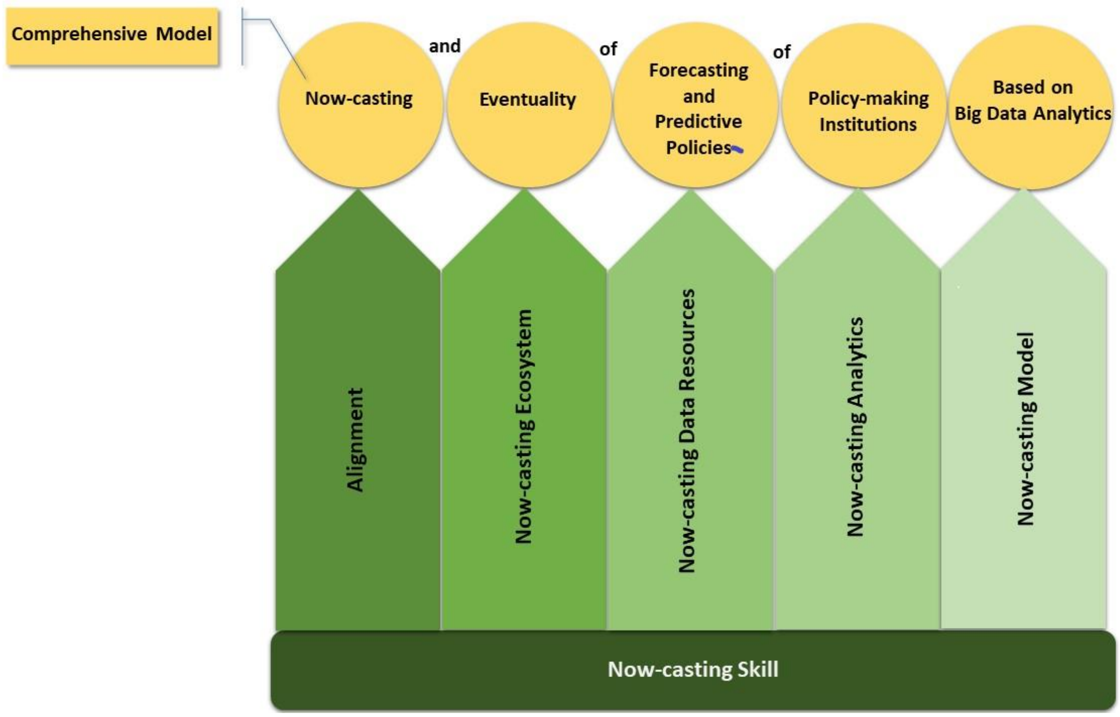

Figure 1. Dimensions of BANC Model

As it is seen in Figure 1, six dimensions of: ‘alignment’, ‘now-casting ecosystem’, ‘now-casting data resources’, ‘now-casting analytics’, ‘now-casting model’ and ‘now-casting skill’ embody 6 basic hypotheses of the research. In

Figure **2**, the composing components of six dimensions are witnessed.

The alignment dimension includes components of the now-casting strategy and the architecture of big data analytics; the now-casting ecosystem dimension includes components of structure, data coverage, repetition and frequency, and type of target indicator; the now-casting data resource dimension includes the type of the resource, type of data, governance of data, quality of data, division and clarification of data, granularity and details; the now-casting analytics dimension includes extraction of big data, process of big data, refinement/ cleansing of big data and analytics of big data and visualization; the now-casting model dimension includes the components of paradigm of modeling, structure of model, parameters of model, tools of modeling, validation of model, revision of data; and now-casting skill dimension includes skills of business, skills of data science, skills of information technology, skills of business-data science, skills of business–IT, IT-data science and skills of business–IT–data science. The now-casting skills cover the other 5 dimensions in terms of knowledge.

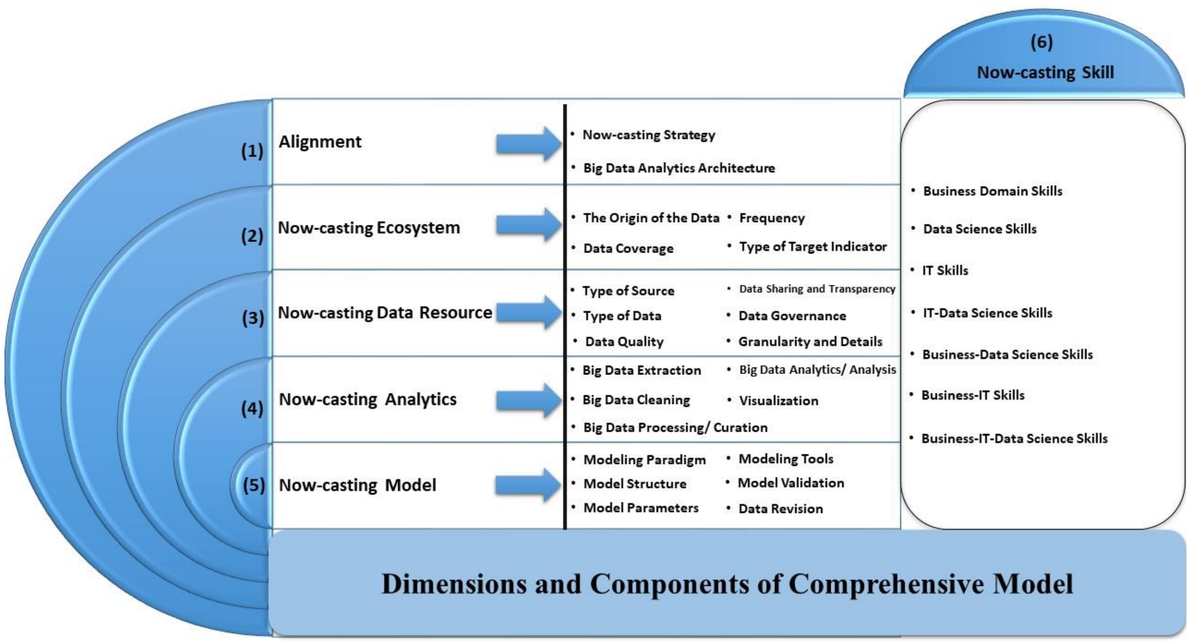

Figure 2. Dimensions and Components of BANC Model

Table indicates the components and indicators of the “Alignment” dimension with references.

Table 5. Components, Indicators, and References of Alignment Dimension

1- Alignment		References
Now-casting Strategy	Business Strategy	Bean (2017) Federal Reserved Bank (2017), Wang et al. (2016), Foster (2016), Baldacci et al. (2016), Kapetanios & Papailias (2016), Sicular (2016), Flood et al. (2016), Scheutz & Mayer (2016), He (2016), Jansen, Jinb, & Winter (2016), Muhlenhoff (2015), Lahiri, Monokroussos, & Zhao (2015), Lahiri & Monokroussos (2013), Tekmedash, Tizro, &
	Big Data Analytics Strategy	
	Value Creation	

	Modeling Strategy	Abyane (2015), Corcoran (2015), Simonson (2014), Jagadish et al. (2014), Einav & Levin (2013), Chen & Zhang (2014), Chen & Lin (2014), Kraska (2013), Elmer (2011), Neely & Sarno (2002), Meese & Rogoff (1983)
	Time Horizon Strategy	
Big Data Analytics Architecture	Standardization	Chernis & Sekkel (2017), Carbone, Jensen, & Sato (2016), Flood et al. (2016), Sicular (2016), Baldacci et al. (2016), Tiffin (2016), Kim et al. (2016), Najafabadi et al. (2015), Dou, Lo, & Muley (2015), Burdick, Fagin, Kolaitis, Popa, & Tan (2015), Chen & Zhang (2014), Jadhav (2013), Faust & Wright (2013), Chamberlin (2010), Hey, Tansley, & Tolle (2009), Bernstein & Haas (2008), Rahm & Do (2000), Pipino, Lee & Wang (2002)
	System Architecture	
	Analytics Architecture	

Table indicates the components and indicators of the “Now-casting Ecosystem” dimension with references.

Table 6. Components, Indicators, and References of Now-casting Ecosystem Dimension

2- Now-casting Ecosystem		Reference
The Origin of the Data	Human-Source	Njuguna (2017), Kim et al. (2016), Baldacci, et al. (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Casey (2014), Galbraith & Tkacz (2016), (Carlsen & Storgaard (2010), Esteves (2009)
	Process-Source	
	Machine-Source	
Data Coverage	Availability	Basel Committee on Banking Supervision (2018), Njuguna (2017), Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Kapetanios & Papailias (2016), Baldacci et al. (2016), Flood et al. (2016), Sicular (2016), MongoDB (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Najafabadi, et al. (2015), Hassani, Saporta, & Silva (2014), Letouzé (2014), Simonson (2014)
	Renewal	
	Continuity of Data Provision	
	Availability of Updated Meta Data	
	Access Cost	
	Possibility of Customization	
Frequency	Continuous Database Update	Chernis & Sekkel (2017), Njuguna (2017), Duarte, Rodrigues, & Rua (2017), Flood et al. (2016), Kapetanios & Papailias (2016), Baldacci, et al. (2016), Jansen, Jinb, & Winter (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Blumenstock, Cadamuro, & On (2015), Doornik & Hendry (2015), Banbura, Giannone, Modugno, & Reichlin (2013), Soto, Frias-Martinez, Virseda, & Frias-Martinez (2011), Blumenstock & Eagle (2010)
	Now-cast Update at a Specified Frequency	
	Number of Samples/ Observations	
Type of Target Indicator	Lagging	Baldacci, et al. (2016), Galbraith & Tkacz (2016), Kapetanios & Papailias (2016), Wang, Xu, Fujita, & Liu (2016), Tiffin (2016), Nymand-Andersen (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Dou, Lo, & Muley (2015), Matta (2014), Simonson (2014), Kraska (2013), Stark & Croushore (2002)
	Coincident	
	Leading	

Table indicates the components and indicators of the “Now-casting Data Recourses” dimension with references.

Table 7. Components, Indicators, and References of Now-casting Data Resource Dimension

3- Now-casting Data Resource		Reference
Type of Source	Official Sources	Njuguna (2017), Kapetanios & Papailias (2016), Wang, Xu, Fujita, & Liu (2016), Kim et al. (2016), Baldacci, et al. (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Blumenstock & Eagle (2010)
	Public Databases	
	Internet-based Data	
	Databases of Financial Institutions	
	Data Vendors	
	Mobile Positioning Data	
	Media and Social Networks	
	Purchase Records	
Type of Data	Real-Time	Chernis & Sekkel (2017), Elaraby, Elmogy, & Barakat (2016), Sicular (2016), Tiffin (2016), Najafabadi, et al. (2015), Tuhkuri (2014), Chen & Lin (2014), Jadhav (2013), Faust & Wright (2013), Lahiri & Monokroussos (2013)
	Historical	
Data Quality	Data Completeness	Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Baldacci, et al. (2016), Kapetanios & Papailias (2016), Carbone, Jensen, & Sato (2016), Nymand-Andersen (2016), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015), Hunter (2014), Dong & Srivastav (2013), O'Connor (2007)
	Data Validity	
	Accessibility	
	Ease of Use	
	Duplication	
	Accuracy	
	Data Integration	
Data Sharing and Transparency	Accurate Data Classification	Flood et al. (2016), Tissot, Baldacci, et al. (2016), Wang, Xu, Fujita, & Liu (2016), Hülagü, Nymand-Andersen, & Suarez (2015), Jagadish, et al. (2014)
	Transparency in Target Variable	
	Variety of User Groups	
Data Governance		Basel Committee on Banking Supervision (2018), Alexander, Das, Ives, Jagadish, & Monteleoni (2017), Foster (2016)
Granularity and Details		Njuguna (2017), Flood et al. (2016), Wang, Xu, Fujita, & Liu (2016), Hoog (2016), Agerri, Artola, Beloki, Rigau, & Soroa (2015), Corcoran (2015)

Table indicates the components and indicators of the "Now-casting Analytics" dimension with references.

Table 8. Components, Indicators, and References of Now-casting Analytics Dimension

4- Now-casting Analytics		**Reference**
Big Data Extraction	Data Attributes in Big Data Big Data Type Extraction Method Data Source Selection based on Now-casting Target	Kliesen (2017), Mauro, Greco, & Grimaldi (2016), Kim et al. (2016), Carbone, Jensen, & Sato (2016), Scheutz & Mayer (2016), Wang, Xu, Fujita, & Liu (2016), Kapetanios & Papailias (2016), Doornik & Hendry (2015), Andersson & Reijer (2015), Objectivity (2015), Najafabadi, et al. (2015), Global Pluse (2013), Maldonado, Weber, & Basak (2011)
Big Data Cleaning	Pre-treatment of Big Data Data Treatment of Big Data	Maldonado, Weber, & Basak (2017), Kapetanios & Papailias (2016), Wang, Xu, Fujita, & Liu (2016), Doornik & Hendry (2015), Najafabadi, et al. (2015), Simonson (2014), Jagadish, et al. (2014), Shi (2014), Chen & Zhang (2014)
Big Data Processing/ Curation	Processing Paradigm Processing Mode Processing Method Algorithm Architecture Processing Tools	Partaourides & Chatzis (2017), Chernis & Sekkel (2017), Nymand-Andersen (2016), Nedjah, Silva, Sá, Mourelle, & Bonilla (2016), Carbone, Jensen, & Sato (2016), Morente-Molinera, Perez, Urena, & Herrera-Viedma (2016), Wang, Xu, Fujita, & Liu (2016), Concurrence (2016), Scheutz & Mayer (2016), Kim et al. (2016), Baldacci, et al. (2016), Tiffin (2016), Elaraby, Elmogy, & Barakat (2016), Najafabadi, et al. (2015), Gandomi & Haider (2015), Hindman (2015), Kundu & Pal (2015), Mahani & Sharabiani (2015), Molavipour & Gohari (2015), Wu, Fan, Peng, Zhang, & Yu (2015), Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos (2014), Schumacher (2014), Chen & Zhang (2014), Zhai, Ong, & Tsang (2014), Simonson (2014), Chen & Lin (2014), Lazer, Kennedy, King, & Vespignani (2014), Lin & Hong (2013), Flood, Mendelowitz, & Nichols (2013), Molinari (2012), Maldonado, Weber, & Basak (2011), Uguz (2011), Soto, Frias-Martinez, Virseda, & Frias-Martinez (2011), Blumenstock & Eagle (2010), Ghysels, Sinko, & Valkanov (2007), Ahrens, et al. (2001)
Big Data Analytics/ Analysis	Match Data Type/ Conformity Type of Analytics Significant Attributes of Big Data in Highly Data-intensive Technologies Analytics Method Analytics Tools	Bean (2017), (Nedjah, Silva, Sá, Mourelle, & Bonilla (2016), Baldacci, et al. (2016), Kim et al. (2016), Elaraby, Elmogy, & Barakat (2016), Houghton & Siegel (2016), Hoog (2016), He, Wu, Yan, Akula, & Shen (2015), Wang, He, Chow, Ou, & Zhang (2015), Ravi & Ravi (2015), Agerri, Artola, Beloki, Rigau, & Soroa (2015), Najafabadi, et al. (2015), Corcoran (2015), Simonson (2014), Varian H. R (2014), Rey & Wells (2013), Yan, et al. (2011), Pébay, Thompson, Bennett, & Mascarenhas (2011), Sahimi & Hamzehpour (2010)
Visualization	Visualization Tools Type of Output	Bean (2017), Sicular (2016), Monteleoni, Schmidt, Saroha, & Asplund (2011), Houghton & Siegel (2016), Scheutz & Mayer (2016), Carbone, Jensen, & Sato (2016), Wang, Xu, Fujita, & Liu (2016), McQuade & Monteleoni (2015), Simonson (2014), Staff (2014), Thompson, et al (2011), Ahrens, et al. (2001)

Table indicates the components and indicators of the “Now-casting Model” dimension with references.

Table 9. Components, Indicators, and References of Now-casting Model Dimension

5- Now-casting Model		Reference
Modeling Paradigm	Deductive/ Inference	Houghton & Siegel (2016), Kim et al. (2016), Elaraby, Elmogy, & Barakat (2016), Hoog (2016), Tekmedash, Tizro, & Abyane (2015), Najafabadi, et al. (2015), Dou, Lo, & Muley (2015), Coates & Ng (2011)
	Inductive	
Model Structure	Timeline of Now-casting	Chernis & Sekkel (2017), He D. (2016), Kim et al. (2016), Hoog (2016), Wang, Xu, Fujita, & Liu (2016), Kapetanios, Marcellino, & Papailias (2016), Baldacci, et al. (2016), Foster (2016), Jansen, Jinb, & Winter (2016), Andersson & Reijer (2015), Neely & Sarno (2002), Orphanides (2001)
	Key Users	
	Systemic Analysis of the Desired System	
	Components and their Interaction	
	Proper, Correct and Available Data Sources	
	Sample Selection	
	Stability in the Target Variable	
Model Parameters	Data Type	Krasser (2018), Galeshchuk & Mukherjee (2017), Njuguna (2017), Kapetanios, Marcellino, & Papailias (2016), Baldacci, et al. (2016), Tiffin (2016), Najafabadi, et al. (2015), Blumenstock, Cadamuro, & On (2015), Matta (2014)
	Variable Type	
	Variable Selection Method	
	Dimensionally Reduction	
Modeling Tools	Tools with New Technique without Coding Environment	Houghton & Siegel (2016), Carbone, Jensen, & Sato (2016), Nymand-Andersen (2016), Wang, Xu, Fujita, & Liu (2016), Hassani & Silva (2015), Madden (2012)
	Modeling Tool as a Computation Engine in a Coding Environment	
	Tools with Traditional Model as an Input into Coding Environment	
Model Validation	Out-of-Sample	Galeshchuk & Mukherjee (2017), Kapetanios, Marcellino, & Papailias (2016), Baldacci, et al. (2016), Hoog (2016), Tiffin (2016), Lazer, Kennedy, King, & Vespignani (2014), Tuhkuri (2014), Dhar (2013), Einav & Levin (2013), Zhou, Sohn, & Lee (2012), Chamberlin (2010), Ashley, Driver, Hayes, & Jeffery (2005), Meese & Rogoff (1983)
	In-Sample	
Data Revision	Produce Different Forecast of the Same Model	Thorsrud (2016), Chamberlin (2010), Brown, Buccellato, Chamberlin, Dey–Chowdhury, & Youll (2009), Patterson (2002), Stark & Croushore (2002)
	Changes in the Estimated Coefficients	
	Model Revision/ Change in Model Specification	

Table indicates the components and indicators of the “Now-casting Skill” dimension with references.

Table 5. Components, Indicators, and References of Now-casting Skill Dimension

6- Now-casting Skill		**Reference**
Business Domain Skills	Knowing the Business Constraints	Wang, Xu, Fujita, & Liu (2016), Nymand-Andersen (2016), Sicular (2016), Hassani & Silva (2015), Tissot, Hülagü, Nymand-Andersen, & Suarez (2015)
	Business Objective and Success Criteria	
Data Science Skills	Quantitative Skills	
	Creativity	
IT Skills	Information Architecture	
	IT Infrastructure	
	Source Systems and their Origin	
	Big Data Management	
IT-Data Science Skills	Coding	
	Data Engineering	
	Data Preparation	
Business-Data Science Skills	Domain Creativity, Passion and Curiosity	
	Analytics Guidance	
	Knowing Intra- and Inter-Industry Collaboration	
Business-IT Skills	Enterprise Architecture	
	Knowledge Markets Requests	
Business-IT-Data Science Skills	Operational Requirements	
	Data and Analytics Governance	
	Graphical Artisanship	
	Storytelling Skills	
	Analytics Leadership	

Materials and Methods

The basic of the BANC model is derived from all mentioned aspects of practical researches, review articles based on challenges, feature of researches, definitions and concepts in three areas of big data, now-casting and policy-making institutions in big data analytics, keywords and executive necessities of researches in the area of big data-based now-casting, strategies, solutions and frameworks. The steps consist of Identifying the main indicators, Conceptualizing and classifying the indicators into components, Classifying the components in the form of dimensions, producing a theoretical framework, Designing the questionnaires, Data gathering and content validity by focused group method, Doing the t-Test after investigating of the normality of data, Forming the hypotheses, Testing hypotheses by publishing a questionnaire for banking industry elites via LinkedIn, and eventually performing statistical tests. Based on the nature of the research, the hybrid method was considered. In the qualitative part, the data collection was done through a focused group method with the statistical samples of academic elites through purposive sampling.

In the quantitative section, the data gathering was done through the survey method with experts, managers and chief elites of IT in banks, credit institutions, and bank service provider companies, through random sampling using Cochran's formula and Morgan's table (n = 178). The data gathering instrument was a researcher-made questionnaire using content validity and

Cronbach's alpha reliability.

For model test based on identified dimensions, 6 following hypotheses were formulated:

Hypothesis 1 – Alignment of now-casting strategy and architecture of big data analytics is one of the dimensions of big data analytics model in now-casting and eventuality of monetary policies of policy-making institutions.

Hypothesis 2 – Now-casting ecosystem is one of the dimensions of the big data analytics model in now-casting and eventuality of monetary policies of policy-making institutions.

Hypothesis 3 – Now-casting data resources are among dimensions of big data analytics model in now-casting and eventuality of monetary policies of policy-making institutions.

Hypothesis 4 – Now-casting analytics is one of the dimensions of the big data analytics model in now-casting and eventuality of monetary policies of policy-making institutions.

Hypothesis 5 – Now-casting model is one of the dimensions of the big data analytics model in now-casting and eventuality of monetary policies of policy-making institutions.

Hypothesis 6 – Now-casting skill is one of the dimensions of big data analytics model in now-casting and eventuality of monetary policies of policy-making institutions.

The statistics of demographics of academic elites are presented in Table .

Table 11. Frequency Distribution of Academic Elites

	Absolute Frequency	**Absolute Frequency Percentage**
1. University		
Azad University	5	62.5
Sharif University	1	12.5
Tarbiat Modares University	1	12.5
Mehralborz Higher Education Institute	1	12.5
Total	178	100
2. Education		
Ph.D.	8	100

The statistics of demographics of industry elites are presented in Table .

Table 12. Frequency Distribution of Industry Elites

	Absolute Frequency	**Absolute Frequency Percentage**
1. Field Activity		
Banks and Financial Institute	44	25
Banking Service Providers	134	75
Total	178	100
2. Organizational Position		
IT Manager	13	7
Bank Officer	10	6
Supervisor	35	20
Chief Operating Officer	24	14
Operations Officer	21	12
Software Officer	31	17

	Absolute Frequency	Absolute Frequency Percentage
1. Field Activity		
Chief Security Officer	6	3
Security Officer	38	21
Total	178	100
3. Working Experience		
1 to 5 Years	37	21
5 to 10 Years	21	12
10 to 15 Years	0	0
15 to 20 Years	108	61
More than 20 Years	12	6
Total	178	100

Using the Likert scale in designing the elites' questionnaire, the indicators whose average scores were more than 3 were used as correct and valid indicators. To evaluate the reliability of the questionnaire Cronbach's alpha coefficients were used. Cronbach's alpha coefficient for the academic elites' questionnaire with 140 questions was 0.951 and for the questionnaire of banking industry elites with 192 questions was 0.982. The score of the alpha coefficient for each questionnaire is higher than 0.75. So the reliability of the questionnaire was confirmed. One-Sample t-Test was performed for the elites' survey.

Research Findings

As the number of variables in this research is high and presentation of microdata that are related to each variable is beyond the scope of this article, it sufficed to present the results at the extent of the hypotheses. The average and standard deviation of elites' replies to each dimension of the comprehensive model along with the results of one sample t-Test are summarized in Table .

Table 13. Mean and the Standard Deviation in Relation to BANC model and the Results of One-Sample t-Test

Hypothesis	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Alignment	4.889	0.333	17.000	1.633	2.145	0.000	Accepted
Now-casting Ecosystem	4.444	0.726	5.965	0.886	2.003	0.000	Accepted
Now-casting Data Resources	4.667	0.707	7.071	1.123	2.210	0.000	Accepted
Now-casting Analytics	4.889	0.333	17.000	1.633	2.145	0.000	Accepted
Now-casting Model	4.778	0.441	12.095	1.439	2.117	0.000	Accepted
Now-casting Skill	4.889	0.333	17.000	1.633	2.145	0.000	Accepted

As it is clear from Table , given the average is more than 3, the dimensions of the comprehensive model for a policy-making institution in the format of 6 hypotheses have been confirmed by academics elites. Therefore, the totality of the presented model in Figure 1 and

Figure **2** is confirmed by academics elites.

To explain the designed model in this research, a summary of patterns and models explored in this research is presented along with the designed comprehensive model based on consideration and comprehensiveness of 6 dimensions and the composing components of the comprehensive model in the form of a matrix in Table 14.

Table 14. The Matrix of Comparison of BANC Model with Frameworks, Solutions, Strategies, and Implementation Steps Presented in Prior Study of the Research

Dimension / Framework/ Solution/ Implementation Steps	Attention to Alignment	Attention to Now-casting Ecosystem	Attention to Now-casting Data Resources	Attention to Now-casting Analytics	Attention to Now-casting Model	Attention to Now-casting Skill
Big Data Life Cycle and Challenges		*	**	**	*	
Big Data Analytics	*	*	**	*	*	
Conceptual Framework			*	**	**	
NIST Big Data Interoperability Framework	**		*	**		*
Solution Path	***		*	**	**	***
Big Data Strategy	***	*				*
BANC Model	***	***	***	***	***	***

* Implicit Mention to Component and Indicators

** Explicit Mention to Component and Identification of its Most Important Indicators

*** Explicit Mention to Component and Full Identification of its Indicators

As illustrated in Table 14, the BANC model is more comprehensive compared to all components mentioned in frameworks, solutions, and strategies and is covered a maximum number of components and their indicators and renders a totality as a model. By observing the above table, it is realized that the concentration of others was mostly on some of the components that are sometimes referred to implicitly and it is not referred to all components of a comprehensive model that converge now-casting and eventuality in a policy-making institution to make policies in the realm of big data analytics.

Application the BANC Model in Industry and the Results

Finding achieved from a more accurate investigation of each component and indicator in policy-making institutions (banks, credit, and financial institutions, and bank service provider companies), are based on Table 15 as follows:

Table 15. Mean and the Standard Deviation in Relation to Dimensions of BANC Model and the Results of One-Sample t-Test

Dimension	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Alignment	2.89	0.476	-2.613	-0.164	-0.023	0.010	Rejected
Now-casting Ecosystem	2.79	0.480	3.094	0.040	0.183	0.002	Accepted
Now-casting Data Resources	3.52	0.507	12.226	0.391	0.541	0.000	Accepted
Now-casting Analytics	2.74	0.549	-6.500	-0.350	-0.187	0.000	Rejected
Now-casting Model	2.76	0.479	-6.499	-0.305	-0.163	0.000	Rejected
Now-casting Skill	3.12	0.370	-0.221	-0.061	0.049	0.825	Rejected

According to table 15, now-casting ecosystem and now-casting data resources with an average of greater than 3 were accepted. In the meantime, alignment, now-casting analytics, and now-casting model with an average of less than 3 and now-casting skill with an average close to 3 were rejected.

A. Alignment Dimension

Based on the results of the t-Test, the alignment dimension (shown in

Table) by the average score of 2.89 was not confirmed in a policy-making institution. The situation of this dimension is illustrated in Table 16.

Table 16. Mean and the Standard Deviation in Relation to Alignment Dimension of BANC model and the Results of One-Sample t-Test

Component	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Now-casting Strategy	2.26	0.46	-21.57	-0.808	-0.673	0.000	Rejected
Big Data Analytics Architecture	3.54	0.48	14.96	0.467	0.609	0.000	Accepted

According to the above table, now-casting strategy with an average of less than 3 was rejected and big data analytics architecture with an average of more than 3 was accepted. The reason for the dimension's invalidity in the component of the now-casting strategy is observed in Table 17.

Table 17. Mean and the Standard Deviation in Relation to Now-casting Strategy of BANC Model and the Results of One-Sample t-Test

Indicator	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Business Strategy	2.792	0.631	-4.40	-0.301	-0.115	0.000	Accepted
Big Data Analytics Strategy	2.768	0.949	-3.25	-0.372	-0.091	0.001	Rejected
Value Creation	2.286	1.095	-8.67	-0.876	-0.551	0.000	Rejected
Modeling Strategy	1.544	0.240	-80.76	-1.492	-1.421	0.000	Rejected
Time Horizon Strategy	2.849	0.708	-2.84	-0.256	-0.046	0.005	Rejected

According to the above table, business strategy with an average of more than 3 was accepted while other indicators were rejected due to an average of less than 3. The reasons for the rejections are as follows:

- Inadequate accuracy on the preparation of a big data analytics strategy to adopt a scientific and engineering approach in this area;
- Inadequate attention on value creation due to ignorance of adopting an insight to make decisions by big data usage and ignorance of using the results of decisions to improve the data and the analytics;
- Lack of a compiled strategy for modeling due to ignorance of determination of techniques like machine learning, discovery optimization, techniques of reducing the dimensions, methods of contraction and decrease estimations and Bayesian or combination of now-casting and also inflexibility and lack of dynamics in learning model of forecasting and struggle to improve refinements and lack of regular and constant updating and determining mechanism of feedback;
- Inadequate concentration in the determination of time horizon strategy due to ignorance of forecasting horizon.

According to Table , the main causes of the distance of architecture of big data analytics components from the average of 5 are lack of standardization of analytical processes, lack of system architecture and determining an accurate framework of the issue in the architecture of analytics and its evaluation.

B. Now-casting Ecosystem Dimension

According to the results of the t-Test, the now-casting ecosystem dimension (shown in Table) with the average score of 2.97 was confirmed in the policy-making institution. The conditions of this dimension's components are indicated in Table 18.

Table 18. Mean and the Standard Deviation in Relation to Components of Now-casting Ecosystem of BANC Model and the Results of One-Sample t-Test

Component	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
The Origin of the Data	1.96	0.28	-50.21	-1.085	-1.003	0.000	Rejected
Data Coverage	3.56	0.63	11.75	0.464	0.651	0.000	Accepted
Frequency	3.62	0.61	13.63	0.533	0.714	0.000	Accepted
Type of Target Indicator	2.76	0.70	-4.64	-0.346	-0.140	0.000	Rejected

As it is seen, the origin of the data and type of target indicator were rejected due to an average of less than 3, and also data coverage and frequency were accepted because of an average of more than 3. The reasons for rejection or distance from an average of 5 are as follows:

- Reasons for rejecting the origin of the data based on the following indicators:
  - Human-Sourced with an average score of 1.168 due to no attention to social network data, images, notes, voice and video files, internet searches and blogs and news archives
  - Machine-Sourced with an average of 1.675 due to no attention to sensors and measuring a machine and recording of events
- Failure of industry and distance from the average of 5 in the component of data coverage, due to lack of accuracy in renewability, lack of access to up-to-date metadata, inadequate accuracy to access cost and lack of possibility to customization or localization
- Failure of industry and distance from the average of 5 in the component of repetition and frequency due to lack of updating of current situation forecasting in a definite frequency and no attention to numbers of daily, weekly and seasonal time observations in the frequency of target indicators
- Rejection of the target indicator due to obliviousness to lagging and coincident indicators and ignorance of leading indicators.

C. Now-casting Data Resource Dimension

According to results t-Test, now-casting data resource dimension (shown Table) with an average of 3.52 was confirmed in the policy-making institutions. The situation of components of this dimension is indicated in Table 19.

Table 19. Mean and the Standard Deviation in Relation to Components of Now-casting Data Resource of BANC Model and the Results of One-Sample t-Test

Component	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Type of Source	3.36	0.52	9.03	0.278	0.433	0.000	Accepted
Type of Data	3.12	0.74	2.22	0.014	0.235	0.027	Accepted
Data Quality	3.99	0.43	31.03	0.929	1.055	0.000	Accepted
Data Sharing and Transparency	4.11	0.49	30.01	1.040	1.186	0.000	Accepted
Data Governance	2.53	1.06	-5.98	-0.631	-0.318	0.000	Rejected
Granularity and Details	4.03	0.81	16.79	0.907	1.149	0.000	Accepted

Although this dimension was confirmed in industry, results of the t-Test for its components shows that all components were accepted, except for data governance due to an average of less than 3. The reasons for industry failure, rejection or distance from the average of 5 are described in the following section and the main indicators of each component are explored.

- Distance to the average of 5 in the component of resource type, due to ignorance of public databases, media and social networks and negligence of internet-based data, data vendors and operators positioning data and purchase records
- Distance to the average of 5 in data type component due to ignorance of real-time data
- Distance to the average of 5 in quality of data due to ignorance of data completeness, data duplication, data consistency, and accurate data classification
- Ignorance of data governance by the policy-making institution

D. Now-casting Analytics Dimension

According to the results of the t-Test, the now-casting analytics dimension (shown in Table) by the average of 2.74 was not confirmed. The condition of this dimension’s components is presented in Table 20.

Table 20. Mean and the Standard Deviation in Relation to Components of Now-casting Analytics of BANC Model and the Results of One-Sample t-Test

Component	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Big Data Extraction	2.97	0.58	-0.69	-0.116	0.056	0.491	Rejected
Big Data Cleaning	2.11	0.81	-14.62	-1.015	-0.774	0.000	Rejected
Big Data Processing/ Curation	2.80	0.54	-4.89	-0.276	-0.117	0.000	Rejected
Big Data Analytics/ Analysis	2.81	0.58	-4.43	-0.280	-0.108	0.000	Rejected
Visualization	3.05	0.53	1.25	-0.029	0.128	0.213	Rejected

As can be seen in the table above, all components were rejected due to an average of less than 3. The reasons for industry failure, rejection or distance to the average of 5 are investigated and the main indicators of each component are indicated as follows:

- Indicators for rejecting big data extraction:
  - Features of big data by an average of 2.597 due to ignorance of variety and complexity of data and ignorance of the degree of being structured (qualitative/quantitative, soft/hard) and ignoring the feature of labeled /unlabeled (categorized/uncategorized)
  - Type of big data by an average of 3.062 due to ignorance of tall, huge and fat big data
  - The method of extraction by an average of 2.681 due to ignorance of statistical method and ignorance of optimization
  - Ignorance of selecting data resources proper to the purpose of now-casting
- Indicators for rejecting big data refinement/ cleansing:
  - Pre-treatment of big data by an average of 1.780 due to ignorance of turning the unstructured data to structured data

  - data treatment of big data by an average of 2.268 due to ignorance of handling the irregularities of data (outliers, missing observations, the impact of workdays, the entrance of periodical and seasonal patterns) and ignorance of removing the deterministic pattern
- Indicators for rejecting big data process:
  - Processing paradigm by an average of 2.855 due to ignorance of batch processing and ignorance of streaming/ real-time and hybrid processing
  - Type of process by an average of 3.342 due to ignorance of process that is sensitive/insensitive to time
  - Method of the process by an average of 2.710 due to ignorance of granular computing and ensemble learning, ignorance of information fusion, lack of feature engineering in the model of automatic extraction and selection (machine learning), ignorance of sampling with data-intensive and application-intensive approach
  - Algorithm architecture by an average of 2.510 due to ignorance of accuracy rate of algorithm forecasting, tackling over-fitting in algorithms when facing noise, confrontation with uncertainties and scalability of the algorithm
  - Ignorance of process tools
- Indicators for rejecting big data analytics:
  - Ignorance of adaption with different data
  - Type of analytics by an average of 2.679 due to ignorance of diagnostic analytics, ignorance of discovery analytics and lack of predictive and prescriptive analytics
  - Significant attributes of big data in highly data-intensive technologies by the average of 3.497 due to ignorance of data variety of data, data value, data volatility, data vulnerability, ignorance of viscosity of data and virality of data
  - Analysis method by the average of 2.024 due to ignorance of using data mining, machine learning methods, artificial neural networks, signal processing, and opinion mining
  - Ignorance of using analysis tools
- Indicators for rejecting visualization:
  - Visualization tools by the average of 3.397 due to ignorance of interactivity and connectivity with various data sources and fitness of tools with business line and lack of commercial tools
  - Type of output by the average of 2.761 due to ignorance of outputs illustrating data discovery, ignorance of visual representation and analytical dashboards, lack of output types like text or storytelling and ignorance of advanced analyses.

E. Now-casting Model Dimension

According to the results of t-Test, the now-casting model dimension (shown in Table) by the average of 2.76 was not confirmed in the policy-making institution. The condition of this dimension's components is presented in Table 21.

Table 21. Mean and the Standard Deviation in Relation to Components of Now-casting Model of BANC Model and the Results of One-Sample t-Test

Component	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Modeling Paradigm	3.30	0.71	5.70	0.198	0.407	0.000	Accepted
Model Structure	3.25	0.44	7.59	0.185	0.314	0.000	Accepted
Model Parameters	2.83	0.47	-4.85	-0.243	-0.102	0.000	Rejected
Modeling Tools	2.40	0.52	-15.31	-0.672	-0.518	0.000	Rejected
Model Validation	2.65	0.76	-6.10	-0.464	-0.237	0.000	Rejected
Data Revision	2.16	0.70	-15.93	-0.941	-0.733	0.000	Rejected

Based on the above table, the modeling paradigm and model structure were accepted because of an average of more than 3. Other components were rejected due to an average of less than 3. The reasons for its failure in the industry, its rejection or distance from an average of 5 are presented in the following section and the main indicators of each component are explored.

- Distance from an average of 5 in model structure, ignorance of now-casting time horizon and key users in the process and ignorance of systematic analysis of the desired system, identification of the elements and interaction among them, selection of sample and stability in the target variable
- Reasons for rejecting model parameters are as following:
  - Type of data by the average of 3.215 due to ignorance of time series and ignorance of cross-sectional data
  - Type of variable by an average of 3.446 due to ignorance of proxy variables
  - Ignorance of method of variable selecting
  - Method of reducing the dimensions by an average of 1.862 due to ignorance of linear reduction of dimensions and lack of using non-linear reduction of dimensions method
- Rejection of modeling tools due to ignorance of proper usage of tools with new technique without coding environment or tools composed of traditional models as the input of into coding environment and also ignorance in the usage of modeling tools as calculating engine into coding environment
- Rejection of data revision due to ignorance of production of forecasting from that model, ignorance in changing the estimation of coefficients of the model and ignorance of shifts in aspects and specifications of the model

F. Now-casting Skill Dimension

According to the results of the t-Test, the now-casting skill dimension (shown in

Table 5) by the average of 3.12 was not confirmed in the policy-making institution. The condition of its components is presented in Table 22.

Table 22. Mean and the Standard Deviation in Relation to Components of Now-casting Skill of BANC Model and the Results of One-Sample t-Test

Component	Mean	Std.	t-Test	Lower	Upper	Sig.	Result
Business Domain Skills	3.77	0.55	18.61	0.689	0.853	0.000	Accepted
Data Science Skills	2.77	0.58	-5.34	-0.321	-0.148	0.000	Rejected
IT Skills	3.68	0.46	19.60	0.615	0.752	0.000	Accepted
IT-Data Science Skills	3.70	0.48	19.40	0.633	0.776	0.000	Accepted
Business-Data Science Skills	2.50	0.51	-13.15	-0.578	-0.427	0.000	Rejected
Business-IT Skills	2.34	0.66	-13.32	-0.756	-0.561	0.000	Rejected
Business-IT-Data Science Skills	2.19	0.41	-26.32	-0.867	-0.746	0.000	Rejected

Based on the above table, the business domain skills, IT skills, and IT-data science skills were accepted because of an average of more than 3. Other components were rejected due to an average of less than 3. The reasons for its rejection or distance from an average of 5 are presented in the following section and the main indicators of each component are explored.

- Distance from an average of 5 in business skills due to ignorance of limitations of business and objectives of business and triumph criteria
- Rejection of data science due to ignorance of quantitative skills and creativity
- Distance from an average of 5 in IT skills due to ignorance of information architecture and ignorance of big data management
- Distance from an average of 5 in IT-data science skills due to ignorance of data engineering and ignorance of data preparation
- Rejection of data science-business skills due to ignorance of domain creativity, passion, and curiosity towards this area, lack of a proper guide for analysis and ignorance of knowing the interaction methods and relationship between inside and outside of the industry
- Rejection of the component of business-IT skills due to lack of enterprise architecture and skills in technology and knowledge regarding existing and emerging markets' demands
- Rejection of the component of business-IT and data science skills due to lack of data governance and data analytics, the skill of storytelling, the leadership of analytics and ignorance of graphic skills

To examine the differences in averages of the research variables, the independent sample t-Test was used. The results of the test among academics and industry members are indicated in Table 23.

Table 23. The Results of Independent Sample t-Test of BANC Model to Compare 2 Groups

Dimension		Leven's test-Sig. (Equality of Variances)	t-Test-Sig. (Equality of Means)	Type	No. of Samples	Mean
Alignment	Equal Variances assumed	0.123	0.000	Industry	178	2.89
	Equal Variances not assumed	-	0.000	University	8	4.88
Now-casting Ecosystem	Equal Variances assumed	0.012	0.000	Industry	178	2.97
	Equal Variances not assumed	-	0.000	University	8	4.44
Now-casting Data Resources	Equal Variances assumed	0.253	0.000	Industry	178	3.52
	Equal Variances not assumed	-	0.000	University	8	4.66
Now-casting Analytics	Equal Variances assumed	0.019	0.000	Industry	178	2.74
	Equal Variances not assumed	-	0.000	University	8	4.88
Now-casting Model	Equal Variances assumed	0.698	0.000	Industry	178	2.76
	Equal Variances not assumed	-	0.000	University	8	4.77
Now-casting Skill	Equal Variances assumed	0.390	0.000	Industry	178	3.12
	Equal Variances not assumed	-	0.000	University	8	4.88

According to the above table, if the significance level of the 'Levene Test' is higher than 0.05, the results of the first row will be used. It accepts the hypothesis of equality of variances of two groups. Therefore, the results of the 'Levene Test' indicate that the significance level of the first line (assuming equality of variances) is used in all dimensions except now-casting ecosystem and now-casting analytics. The results of t-Test in the first and second lines indicate that in all investigated dimensions by the confidence of 95 percent, there is a considerable difference between responses of academic respondents and industry respondents. In other words, in all dimensions of the model, the average academics' opinions are higher than industry respondent's opinions. Therefore, the lack of attention of the industry towards all the six-dimensional components is evident.

Conclusion and Recommendations

This research has been aimed at providing a comprehensive model in two areas, big data analytics, and now-casting, with the goal of convergence between them and maximizing the level of accuracy of the policy-making institution in decision- and policy-making. Based on this, the basic dimensions, components, and indicators of the comprehensive model in the policy-making institutions were recognized and the model was designed. The proposed model; BANC Model, applies to all policy-making institutions with a now-casting and data-driven approach. This article discusses the situation of each dimension and mentioned component of the designed model in the banking industry of Iran. According to the results of the comprehensive model use and its significant difference in the industry, the following recommendations are proposed to cover the gaps and shortcomings to the banking industry:

- Consideration of value creation in bank industry signifies the importance of intelligent management and the influence of analytical strategies on business and since big data from the policymakers' point of view is considered as a new type of strategic resource in digital era, owning a valuable potentiality, preparation of a strategic program and the map for this path, and the most crucial of all, a strategic thinking are key components in activities of policy-making institution to provide functional programs matched with policy measures. Moreover, creating the mechanism of the decisions' results feedback will provide a proper ground for improvement, correction, and completion of plans;
- Since there is a high variety of data in big data paradigm, advanced technologies, and new techniques are provided that innately and intrinsically have great speed. Therefore, to make correct policies about how to exploit the opportunities of big data analytics and to gain better results, human skills as the most significant progressive factor for policy-making purposes, should be taken into account. It is recommended to invest purposefully in earning the skills in this area. Paying attention to innovations, creativities and determining proper strategies in business can affect personnel's skill level;
- Consideration of the origin of the data regarding the growth and variety of data space is necessary to be revised by the policy-making institutions to provide the opportunity of a more accurate estimation of target indicators of the area through a technical approach
- The policy-making institution has to recognize and apply proper data resources especially, real-time resources and revise the interactive activities by real-time data to reduce risks of ignorance of accurate estimation of current conditions of target indicators;
- The policy-making institution has to apply new and automatic nonlinear methods of feature engineering and to use noises in real-time data and also to exploit new modeling tools and to consider data inclination and eventuality (data and event-driven) in modeling; and
- It is necessary to consider the highly data-driven technologies and to use new methods of analysis like machine learning and visualization tools with the ability of interaction and connection to different data resources with varieties of data regarding the type of big data aimed at reducing the risks of policy-making institution's investment in the field of IT.

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