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Human-centric analytics: A framework based on the confluence of cognitive science and data science in business and management

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Abstract

In this paper, a framework is presented to use data science to analyze human behaviour and cognition mechanisms in organizations. To obtain the goal in any business, it is essential to manage people, whether they are intra-organizational or extra-organizational. The objective of such management is to enhance people's behaviour by identifying the influencing factors and mechanisms. The paper aims to present a framework that consists of three science domains: a) organizational and management science, b) cognitive science, and c) data science. The goal of that framework is to identify the cognitive mechanisms and cognitive factors of different groups of people to enable performance improvement within an organization. This framework is described by reviewing data science and machine learning techniques and how they are applied to the framework. To explain the conceptual framework and bring examples, UNICEF's country office in Iran, with its intra- and extra-organizational people, is used. Bringing together previously mentioned science domains in pairs has resulted in new facets of scientific growth in multiple fields. The main idea is that the confluence of all domains will develop a new framework for analyzing the mental and professional skills and capabilities of each group involved in the organization. In this framework called Human-Centric Analytics (HCA), which is described as the main finding of this study, data science is used as a scientific approach, and by using cognitive theories and human-related datasets, the goal is to achieve analysis that can help organizational achievements by considering the cognitive capabilities of human capital. The present paper is the first publication of a comprehensive and major research project. This research relates to two purposes after introducing the mentioned framework. On one hand, this framework can be used and customized for organizations to improve their performance, and on the other hand, it opens a new perspective for researchers of the three main scientific domains to expand their research and conclusions.

Keywords: Management, Information system, Data Science, Cognitive Science, Systematic Framework, Business
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1 Introduction

This paper aims to present a new idea in analyzing businesses. The idea is to present a framework for designing information systems that emphasizes all stakeholders of all sizes of organizations, whether they are internal or external.

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The need for this type of analysis has a deep and wide history and background. Many types and categories of analysis based on various theories have been developed to answer such needs. In every analysis, there must be a way of measuring something, and for each of the analyses mentioned, there were parameters and factors based on their begotten theories.

Human-Centric Analysis, as its name implies, is primarily concerned with, measured, and focused on people/human. People are key resources and factors in any business. These people behave, think and play their roles based on their cognition mechanisms and psychological aspects. These factors ideally can be measured and analyzed by many data and advanced methods. Some of these methods are already developed under data science, machine learning, and artificial intelligence science domain. Those cognition mechanisms and psychological aspects are being studied by cognitive science.

Human Centric Analysis is a framework for managing and making decisions in a way to increase the efficiency and profit of an organization by assuming that effective people on processes are key factors. For example, considering a commercial organization, the customers and suppliers are the most important factors. The pricing, marketing, advertisement campaigns, inventory, and many other processes are affected by how these groups of people think, behave and feel. Or consider investing in financial markets because of supply and demand theory, all of the technical pricing processes are affected by the behaviour and cognition of shareholders. Or on the other hand, considering governmental organizations best way for policy making, countrywide administration, ruling, law-making, etc, is to understand and predict the people's needs, behaviour, and cognition of every aspect. Considering any type of organization changes the key groups of people based on their goals, aims, and processes, but doesn't change the fact that analyzing and predicting these groups can be the main factor in increasing the efficiency of the organization and smoothing the path to reaching the goals.

Ideally, describing, predicting, and analyzing the behaviour and cognition of all groups of people, whether intra- or extra-organization is the key to the best management ways in every organization. This can be achieved by using data science approaches, machine learning techniques, and implementing artificial intelligence technologies on all related data about the people to help the management. Note that managers themselves are a group of people, as one of the intra-organizational stakeholders.

The main goals of introducing the Human-Centric Analysis framework can be summed up as:

1- Structuring and standardising the whole way of analyzing each organization to optimize the management of people and for the people:

Having such a structure and approach helps the organizations in paying more attention to the people, codification of using data about the people, decreasing the costs of analyses, and giving analyses the potential to be customized for the organization and its needs. Without such a framework, each organization that is after using data-driven analytics should develop its own system or use existing analytics, whether proprietary or open-source. When an organization goes about developing its system in many ways it is forced to reinvent the wheel. When it comes to using existing analytics they should be customized for their needs. But if the Human-Centric Analytics idea gets used, then an organization can develop a customized and to-the-point analysis system without reinventing the wheel, using others' experiences and opinions, and integrating existing analytics systems.

2- Making the people-oriented management more and more scientific:

In the decades between 1930-1960, many neo-classical theories and studies, like Hawthorne studies, Theory X and Theory Y by McGregor, Barnard's Cooperative System, etc, showed the importance of paying attention to people in management. These days, the importance of managing the organization in more organic ways instead of mechanically is obvious to everyone. But managing in such a way needs to be supported by many science domains, from human sciences to technical and engineering sciences. One of the Human-Centric Analytics aims is to make this type of management and analysis in every organization scientific without increasing the costs of managers' and analyzers pieces of training.

3- Declaring new subjects for researchers in various science domains to participate in developing these analytics:

Researchers from all of the science domains involved in Human-Centric Analytics are after developing their methods and subjects in their proficiency and specific domain. But having a framework that considers all of these domains and provides the goal of research from the confluence of these domains makes the research way smoother and more efficient. By developing this framework, the researchers from the various fields can study different subjects and methods and integrate their goals with each other.

Humans are one of the most important parts of every organization or business. They can be either in or out of the organization, or in any way, can be stakeholders. So there is a great need to manage them appropriately.

Intra-organizational means within an organization. This would mean that people or departments within an organization are working together or collaborating. In intellectual capital literature [38, 43], intra-organizational people, at any organizational level, play one of the most important roles. There is another important concept known as organizational behavior. The subject of this scientific field is man's behaviour, decision-making, and reasoning in organizations.

Extra-organizational means within an organization and its environment. This would mean the people and relations that are outside the border of an organization but related to it. Many other important issues are brought up when studying humans outside the organization, like customers [7], suppliers, stakeholders, and their roles, besides the social capital of the organization. In general, the value of finding a scientific framework to study and predict human cognition and the effect of human behaviours on business is obvious.

Humans cannot be assumed to have absolute rationale, but still, their cognition based on their decision making and reasoning [45] can still be studied [35]. Cognitive scientists and psychologists have the challenge to validate and verify if human reasoning is rooted in deductive reasoning and performance [26]. Kingstone has introduced a new research framework called 'Cognitive Ethology' for verifying and validating theories of cognitive and behavioural sciences [29].

Understanding the cognition mechanism of humans can help to it being managed better. Human is an important part of every organization and business, which can't be overlooked when managing and analyzing the organization. People in any organization, either intra-organizational or extra-organizational, play important roles in achieving the desired situation and goals. These roles are performed by a quality that is influenced by cognitive parameters.

Data Science is the science of using data, but not studying the data. Data mining is an interdisciplinary methodology lying at the interface of statistics, database technology, programming, machine learning, and other areas [18]. Finding patterns, future studying, predicting, exploratory data analysis, knowledge discovery, creating expert systems, reasoning, and many other elements are served by data mining.

Big data is a set of techniques and technologies which require new forms of integration to uncover large hidden values from large datasets that are diverse, complex, and of a massive scale [19]. Big data is recognized by its 4Vs: Volume, Variety, Velocity, and Veracity (or value). Today, big data is highly generated by people when interacting with any kind of IT platform.

To achieve its purposes, data science uses not only many methods such as machine learning algorithms for selecting, preprocessing, transforming, mining and knowledge discovery, evaluating and visualising data, but uses big data as well.

Obviously, the cognitive science domain has parameters to study and predict human behaviour. Human behaviour is one of the most important elements of the business, and so analyzing it is essential. This analysis opens a new door to the four functional facets of data analytics: descriptive, diagnostic, predictive, and prescriptive. But how efficiently can these parameters be used in the analysis?

Considering the data science approach, analyzing cognitive data has two aspects. The first one consists of a lot of big data generated by humans when interacting with virtual environments such as social networks [10], organizational systems [24], simulation programs, gamification systems, etc. These sets of big data can be used to be studied by machine learning methods and visualized by the data science approach. The second aspect is the data gathered from physical sources like RFID or IoT powered devices, which are used by humans when interacting with the real environment, like Amazon Dash Carts [3] or industry 4.0 usages [12].

This study introduces an interdisciplinary framework, which is illustrated as a star in Figure 1, to study the human facet of business using data-driven approaches and methods.

In this study, three domains of science, a) business/organization sciences, b) cognitive science, and c) data science, are considered. Each of these two domains has an overlap that generates a new domain. For example, the overlap of cognitive science with the science of business and organizing represents other domains such as organizational behavior or concepts like intellectual capital. Overlapping of data science and organizational science for example represents business analytics and business intelligence. When cognitive science and data science overlap, new domains such as studying intelligence or organizational learning can be mentioned.

2 Cognitive Psychology and Organization

There are some interesting subjects in cognitive psychology that can be focused on in the management and organization science domain. Among these subjects, perception, attention, short-term and long-term memory, visual imagery, language, problem-solving, judgment, decision making, and reasoning can be named. These subjects are very

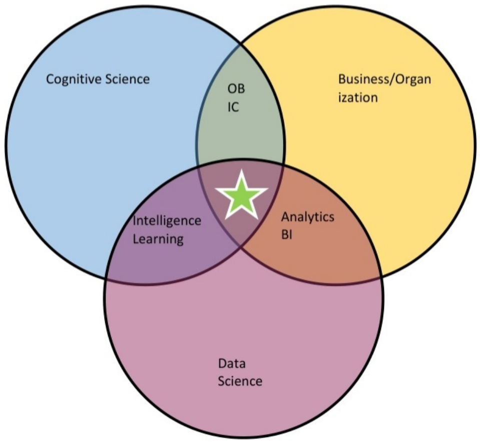

Figure 1: The interdisciplinary framework

important in the cognitive analysis of any organization, whether focusing on intra- or extra-organizational people. For example, for any organization, besides being for-profit or nonprofit, customers are key extra-organizational people. Knowing how and what their perception is, what they pay attention to, how they imagine, their decision-making and reasoning mechanisms are, and many other of these facts are very important for managing, measuring, and controlling the current situation and also defining the desired situation and the path to make the desired situation.

Perception in organizations was considered times ago. In the organizational behavior domain, this concept is considered for improving intra-organizational people [21] and considered to improve the loyalty of extra-organizational people [5]. Yet, this concept is still a big concern in organizations. Advertising effectiveness [31], organizational citizenship [28], improving leadership [4], and many other subjects are just some case examples of this concern.

In general, subjects mentioned from cognitive psychology and science have confluence with many subjects from organization and management, like knowledge management, user experience, employee performance, customer loyalty, branding, and also every other subject which is related to humans in organizations. Using cognitive data and data science methods to manage an organization or business yields to the cognitive analytics part of the Human-Centric Analytics framework.

3 Using Machine Learning

Machine learning techniques can be widely used in studying human cognition and behaviour. This calls for mining the data generated by humans voluntarily and involuntarily. Naturally occurring datasets can be mined for different purposes. Studying human cognition with data mining techniques can be performed, for example, by corporations to target marketing [8] and by governments to allocate resources [13]. However, cognitive scientists and psychologists have not yet fully utilized these data and machine learning techniques [37]. Using machine learning to mine datasets for prediction, analysis, or pattern recognition is essential. Here, mining these datasets and applying machine learning techniques is aimed at analyzing business and developing cognitive analytics.

3.1 Machine Learning Types

The learning algorithm in machine learning is divided into three major groups: supervised and semi-supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, one of the main goals is creating a classifier by building a model of class labels, predictor features, and their relations. The resulting classifier can be used to label classes with unknown class labels and known values of predictor features [30]. Unsupervised learning uses datasets without any labels, relying only on inputs to find structure or patterns in the dataset. These patterns can form clusters.

In quantitative studies, there are two types of variables: discrete and continuous. If a variable can take on any value between two specified values, it is called a continuous variable; otherwise, it is known as a discrete variable. In the context of machine learning, based on the data type used in the algorithm, some techniques can be used for both or just for one of the types.

The general application of machine learning types, extracted from reviewing papers and other studies, is illustrated in Figure 2. Each of these general applications has many specific applications in cognitive analytics and the Human-Centric Analytics framework.

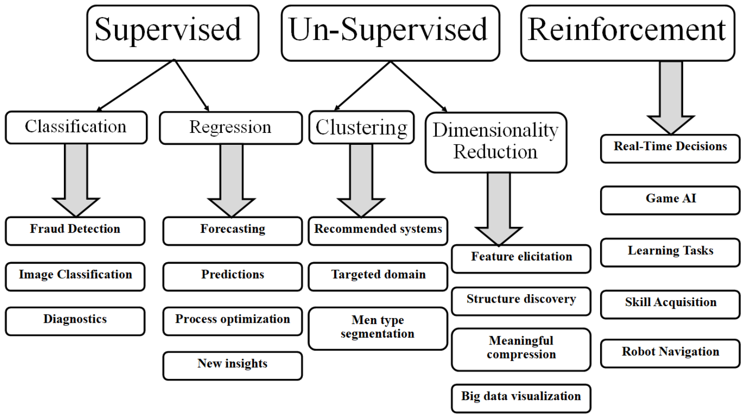

Figure 2: General applications of Machine learning types

Some of the most commonly used machine learning algorithms in cognitive applications are illustrated in Figure 3. In this figure, the algorithms are categorized by their learning type and data type. The algorithms in the deep learning category can use both data types, discrete and continuous, and in general, they are used more for optimizing, feature extracting, and developing hybrid algorithms than for learning and pattern recognition.

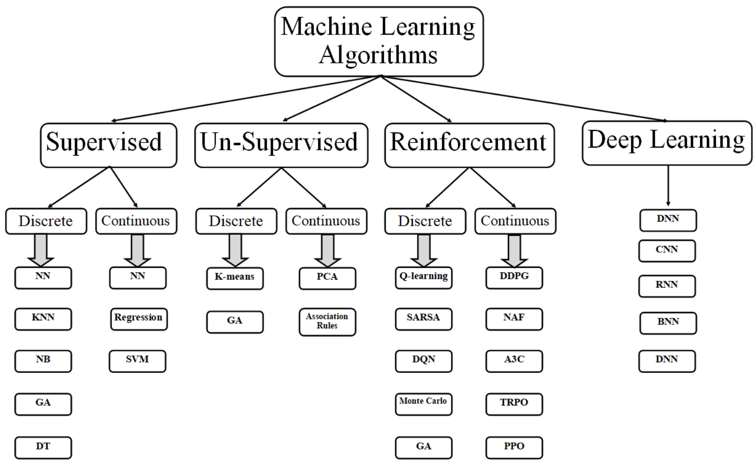

Figure 3: Machine learning algorithms categories

3.2 Machine learning methods

Regression analysis, as a supervised machine learning technique, is a basic method to make relations between variables. In any data-driven study and analysis, there are dependent and independent variables. Regression analysis creates a linear or non-linear function with these variables. With such a function, the dependent variable can be predicted, and by tracking the influence of the independent variables, it can be prescribed and controlled. Using this method with cognitive variables and parameters can result in cognitive analytics. As an example, studying cognitive sequential dependencies by human judgment data [48] can be mentioned. In Vinson's study, users' ratings on the information system can be refined from their biases using the last ratings.

3.2.1 Neural networks

There are a lot of machine learning methods using neural networks. Artificial neural network, deep neural network, convolutional neural network, recurrent neural network, spiking neural network, and quantum neural network are among all machine learning methods that use artificial neural networks. Each of these has its own bold usage in cognitive domains.

Artificial neural networks are computing systems inspired by the biological neural network of the human brain. Using this network, in general, is a supervised machine learning technique. After training the network and the learning stage, the network can be used for a variety of tasks in classification. Note that these networks can even be used for clustering tasks. Problems solved by ANNS are, in general, based on pattern classification, clustering, function approximation, forecasting, and association, like image completion [6].

Deep learning architectures such as deep neural networks, deep belief networks, and recurrent neural networks are based on ANN computing systems. Learning can be supervised, semi-supervised or unsupervised. These architectures have many applications. Various deep neural networks are widely used in automatic speech recognition, image processing, natural language processing, and recommendation systems. In cognitive science, all of these applications are important and practical. Human cognition can be recognized by studying man's behaviour. Image processing, speech recognition, and natural language processing have a direct impact on this behaviour, so they can be used in cognitive analytics. For a cognitive analytic system, parameters such as occupational stress, health, and security, etc., can be studied in the organizational behavior domain, and parameters such as perceived service quality, text message sentiments, etc., can be studied in customer relationship and partnership management.

3.2.2 Evolutionary Algorithms

Cognitive science discoveries and interests in neural networks in computer science have offered a lot of advantages in machine learning systems [17]. Evolutionary algorithms are highly inspired by biological evolution, such as reproduction, mutation, recombination, and selection. Techniques like Ant colony optimization, Artificial bee colony, Cuckoo search, and Genetic algorithms are all evolutionary algorithms.

Genetic algorithms are probabilistic processes in searching and optimizing tasks. Their most significant advantage is the possibility of using them in big spaces such as states, which can be demonstrated by strings [17]. Genetic algorithms are widely used in prediction, classification, and information retrieval [11]. Genetic programming is being used in control engineering and systems [32] and can be used to develop cognitive systems [40] [22].

3.2.3 Classifiers and Clusterers

Classification is one of the most important tasks in any cognitive analytic system. This task can result in many to-the-point goals of these systems by using the most available data, like sentiment analysis of a peer review by just its text classification [50]. This task is a supervised process that can be implemented on every type of data, such as text, image, audio, etc. Classification of these data is useful for sentiment analysis, studying cognition mechanisms of humans, human behaviour parameters such as stress, etc. Having this kind of information is useful and important in developing a cognitive analytic system for a business. Classifiers like decision tree, k-nearest neighbour, and support vector machine are basic available methods of classification.

Clustering is an unsupervised process of making groups of data and information. Like classification, clustering can also be implemented on every type of data. Clustering data in cognitive analytics is highly appreciated. Furthermore, data has metadata which can be studied as information in each cluster. Studying these clusters and their metadata is another important task in a cognitive business analytics system that can result in grouping intra-organizational humans, partners, customers, etc.

3.2.4 Hybrid Algorithms

Most machine learning algorithms in Table 1 are for specific datasets or tasks that are concluded in Figures 2 and 3. But combining different algorithms or using some of them together as one individual algorithm can improve the performance by elements like generalizing and adapting to new tasks [1]. These hybrid algorithms can also be used just for optimization and improving feature extraction. Combining algorithms and techniques like artificial neural networks, evolutionary algorithms, and fuzzy logic, with some classifiers or cluster makers, is common and practical. It also creates hybrid machine learning methods [15] [36] [27]. Sometimes the hybrid method is just combining classification and classification or clustering and classification [46].

Table 1: Hybrid Algorithms

Constitutive Algorithms	Use Case Examples
Fuzzy set theory–Neural networks–Decision tree [16]	Prediction in chaotic conditions
SVM–Fuzzy set–Neural networks [33]	Pattern classification
Genetic-fuzzy [41]	Prediction
SVM–KNN [44]	Classification
Hidden Markov Model–Fuzzy logic[42]	Non-English character recognition
Association rule algorithms-Genetic algorithm [29]	Tree induction and prediction
Types of Regression–Support vector-Artificial neural network [3]	Simulation
Ensemble methods (AdaBoost, Bagging, Dagging, MultiBoost, Rotation Forest, and Random SubSpace) – Multiple perceptron neural network [49]	Optimization
Association rule–Types of Regression–Clustering [20]	Increasing accuracy in detections and pattern recognition

4 Human and Cognitive Science in Business, Organization, and Management

The brain and cognition system of organization managers, as humans, plays a significant role in shaping their management policies and organizational behaviour. While the brain is a crucial element in determining behaviour and emotional processes, other factors such as the body, society, and resources also contribute. Social, cultural, and environmental forces are among the components that can be mapped to the brain, body, and mind to analyze the cognitive and emotional processes of individuals within organizations [20]. It is evident that the brain and cognition system of all individuals, whether inside or outside an organization, significantly impact the organization's management and analytics.

Viewing all intra- and extra-organizational individuals as integral parts of the organization leads to the identification of numerous roles and tasks that must be managed effectively. Each group of individuals has distinct roles, tasks, and activities. Organizations can categorize these components based on their specific needs, infrastructure, and capabilities. The interdisciplinary framework introduced in this study should be applied to each organization according to its unique context. To better illustrate the Human-Centric Analytics framework, several examples are provided, followed by recommended actions for implementing this categorization within the interdisciplinary framework.

For instance, consider a country office of UNICEF, an international non-profit organization. This example is not a case study, nor has any research been conducted on this specific office. However, UNICEF is chosen for its international recognition and the diversity of its intra- and extra-organizational stakeholders. UNICEF country offices operate under regional offices, which are managed by the headquarters [47]. In this example, we focus on one country office and its intra- and extra-organizational stakeholders. Each organization, based on its purpose and type, has unique groups of individuals. Interviews with UNICEF country office personnel reveal that, as a non-profit and non-governmental organization, UNICEF comprises various groups of individuals, each with distinct roles, tasks, and activities. The ultimate goal of identifying these groups and their cognitive tasks is to analyze them using data science approaches. While it is not feasible to include all groups in this study, the most significant ones are selected. In practice, organizations have access to diverse information and can consider all relevant groups. Table 2 presents some key intra-organizational groups within the UNICEF Islamic Republic of Iran country office.

In the UNICEF country office, all staff are divided into two divisions: operations and programs. Each division has its head, and both work under the supervision of a Representative who is in charge of the whole office. In UNICEF, as an NGO and Non-Profit Organization, the main goal is to improve the quality and quantity of services for children. These services include charity, research, organizing, funding, etc. The organization is after finding the main influencing cognitive parameters in intra-organizational people's activities. Assuming any mission, the organization must have a set of specific goals to enable it to achieve its desired situation. Some outcomes of key activities of intra-organizational people assist UNICEF in getting closer to the goal. The chosen activities and approaches should be described, predicted, and prescribed. Then, once data science methods are applied, a cognitive analytics solution can be introduced for the organization. As well as the intra-organizational people's activities, the UNICEF expects some specific behaviour from extra-organizational and is after the main influencing cognitive parameters in those activities. For example, in a hypothetical case, UNICEF helps the government and the Ministry of Education educate autistic children. Here, UNICEF can provide international research and experience. In Table 3, the key extra-organizational people are shown.

Table 2: UNICEF country office intra-organizational key people

Division	Role	Task	Activities
Operation	Managerial [12]	Knowing the Programs division needs	Decision making, Communicating, Choosing, Feeling, Teaching etc.
		Monitoring operations	
		Allocating resources	
		Leading	
	Executive	Providing the needs of other groups and departments, like IT, Security, Transportation, etc.	
Program	Managerial	Providing the operation division with the program's needs	
		Leading	
		Monitoring the projects	
	Researching	Researching	
		Creating Knowledge-base	
		Providing the needed solutions to other groups	
	Representing	Preparing presents	
		Giving Speech	
		Improving Social capital	
		Communicating with extra-organizational groups	
	Field Executive	Implementing solutions	
		Communicating with extra-organizational groups	

Table 3: UNICEF country office extra-organizational key people

Group	Organization's expectation	Activities
Representative of the ministry of education	Collaborating in knowledge transfer and implementing it	Learning Teaching Perceiving etc.
International researchers	Collaborating in knowledge transfer	
Government	Providing suitable environment and infrastructure	
School staff	Learning from the experts and implementing	
Autistic students	Improving the learning and education	

5 Utilization of machine learning algorithms in cognitive analytics

As mentioned before, there are several machine learning types, and each has its general applications. Here, the main aim is to use these techniques in the cognitive approach to studying business more effectively. Based on categorized applications in Figure 2, the specific application of each category in the domain of cognitive science is equalized for business studies in Table 4.

Table 4: Specific application of each machine learning algorithm type

Machine learning type	Task type	Specific application
Supervised Learning	Classification	Creating people type and classifying them in these types
		Classifying of Behaviors and its consequence
		Sentiment Analysis
		Classifying cognitive theories' inputs such as images
	Regression	Finding trends and patterns in cognitive parameters
		Predicting behavior and cognition of people
		Forecasting and functional analysis
		Finding new insights
Unsupervised Learning	Clustering	People segmentation
		Finding domain to focus on
		Finding relation between different types of clusters
	Dimensionality Reduction	Visualizing BONDS[10]
		Cognitive feature extraction
		Structure Discovery
Reinforcement Learning	Reinforcement Learning	Real-time decisions
		Decision making using AI and expert system
		Skill acquisition in the cognitive domain

Having cognitive analytics system in the UNICEF case

UNICEF can now use data science approaches and big data sources like social networks to create a relationship between main activities and organization's expectations and staff tasks. Then, by using machine learning techniques, the organization can find the main cognitive parameters influencing the quality of the activities. The ultimate goal is to have cognitive analytics for achieving organizational goals. These goals can be presented in projects or as general goals of the organization. The path to the ultimate goal is summarised in Table 5.

Table 5: Stages of reaching the cognitive analytics and use of each science domain of the Human-Centric Analytics framework

Stage	**Phase**	**Using Data Science**	**Using Cognitive Science**	**Using Organizational Science**
1	Assuming an organizational goal	No	No	Yes
2	Grouping the key intra- and extra-organizational people related to the goal	No	Yes	Yes
3	Finding the main activities of people	No	Yes	Yes
4	Mapping activities with the task or organization's expectation	Yes	Yes	No
5	Finding influencing parameters on the quality of activity	Yes	Yes	No
6	Perform descriptive, predictive, and prescriptive analysis on last stage parameters for the desired situation	Yes	No	No
7	Creating cognitive analytics	Yes	Yes	Yes

The cognitive analytics mentioned in the last stage of Table 5 consists of business intelligence and business analytics of the desired situation, the path to desirables, important factors, and decision-making methods, all based on the influencing human's cognition and cognitive process.

6 Introducing the Human-Centric Analytics framework

The need for the framework is explained in detail in the previous parts of this paper. In this part, the framework can be introduced independently and in detail. The Human-Centric Analytics framework has three domains of science: a) cognitive science, b) data science, and c) management and business. The properties, scope, and aim of each science domain of this framework are introduced in Table 6.

Table 6: Characteristics of science domains in Human-Centric Analytics framework

Science domain	**What to study**	**Aim of studying**	**Example**
Cognitive Science	Intra-organizational human cognition and behavior	Increasing human resource and intellectual capital performance	Improving human resources intra-organizational learning and increasing people's knowledge
	Extra-organizational human cognition and behavior	Adapting business and organization strategy	Predicting customer behavior and improving marketing scope
Data Science	Methodologies using organizational data	Understanding and finding patterns in data regarding people's interaction with the organization	Using data stored from the Customer Relationship Management system
	Methodologies using data gathered from devices	Understanding and finding patterns in data regarding people's interaction with the organization	Using data stored from IoT powered devices in a hypermarket
Organization, Business, and Management	Human as intellectual capital	Increasing human capital performance	Decreasing occupational stress
	Business analytics and Business intelligence	Helping managers and improving decision making	Integrating business intelligence dashboard with cognitive data of customer behavior
	Strategy and planning	Optimizing business planning and prescription	Improving business strategy dealing with partners, suppliers, and other stakeholders

Overlapping of different science domains is illustrated in Table 7 as a matrix. Each cell is a paired overlap of two science domains of the Human-Centric Analytics framework.

Table 7: Overlap of each science domain with others

	Cognitive Science	**Data Science**	**Business and Management**
Cognitive Science	-	Using what we know about the brain and human cognition mechanisms to develop data science algorithms like what is concluded in ANNs	Better understanding organizational behavior and managing human resource
Data Science	Using Data science	-	Using Data science
-	methodologies to understand cognitive theories like mining big data of social networks for verifying a psychological and cognitive theory	-	approach in business analytics like descriptive, predictive and prescriptive. And creating better business intelligence
Business and Management	Validating and verifying psychological theories using the organization as a lab	Developing better data mining models with understanding business models and organizational planning	-

6.1 Using the Human-Centric Analytics Framework in Business Analytics and Management

In our framework, we focus on business analytics based on the cognitive science domain related to humans, utilizing data mining methodology. Watson IBM categorizes business analytics into five levels: Descriptive, Diagnostic, Predictive, Prescriptive, and Cognitive analytics [25]. Data mining methodology has been widely used in information systems, such as Management Information Systems (MIS), Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Supply Chain Management (SCM), and others, to improve human resources management and/or capital improvements [44]. In this framework, management science, cognitive science, and data science are respectively the goal, tool, and method of analytics. It implies that to achieve a goal and improve management, using data science approaches based on cognitive science theories and data is essential.

Every organization, based on its own goals, can pursue analysis and management by applying this framework. The main difference in various systems and organizations lies in the people groups and cognitive parameters. For a trading firm, customers and suppliers are prioritized as extra-organizational people, so cognitive analytics focuses on finding the influencing parameters that lead to better sales for the firm. However, for an educational organization like schools, students are both intra- and extra-organizational people who play a very important role, alongside teachers as intra-organizational and parents as extra-organizational people. Cognitive analytics in such an organization aims to find and manage parameters that lead to a better educational system. Likewise, every organization can identify its groups and goals and then apply this framework. In Figure 4, the framework is illustrated in sequential stages, and the use of machine learning techniques for each stage is shown.

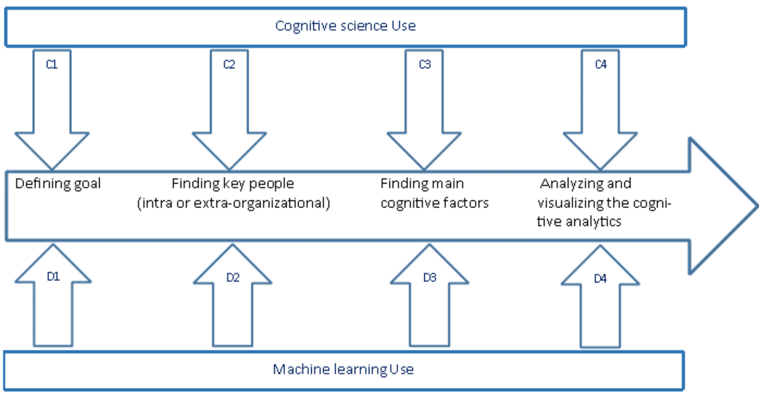

Figure 4: Stages of using the framework in any organization

In Figure 4, sequential stages of using this framework in business analytics and management are illustrated. Details of each stage are extracted from three science domains of Management, Cognitive Science, and Data Science. As concluded in Table 8, each stage has a particular use of cognitive and data science. In the first stage for defining the goal, the managers' decision-making should be optimized, and the manager should be able to use classified information. In the second stage, to find the key people, the manager is not expected to know either every person involved or the psychological methods. In this stage, the system should be able to cluster people automatically and help the manager to find and choose the key people. In the third stage, after the key people are found and introduced, it is important to realize the main cognitive factors to improve the quality of roles, tasks, and activities of people. In the last stage, by having all previous stages' data and information, the analytics and business intelligence system helps the manager to optimize data-driven decision making.

Table 8: Figure 4 Notation

Stage	**What to do**	**Stage**	**What to do**
D1	Supervised and reinforced learning for finding, verifying, or optimizing the goal using inter-organizational data	C1	Using cognitive theories for optimizing manager's decision making
D2	Unsupervised using data of information systems and extra-organizational data such as social networks	C2	Describing the role, task, and organization's expectation and introducing the groups
D3	Unsupervised and reinforced learning using naturally occurring data sets	C3	Defining cognitive parameters influencing the goal
D4	Visualizing and storytelling with data	C4	Visualizing the cognition mechanism and cognitive factors and the relation between them and business's other data

In D1, the supervised machine learning is chosen since, for defining the goal, the manager's insight is highly valued. In these methods, the whole system will allow the manager to make more intelligent decisions for defining the goals. The cognitive information that is recommended to be used is for the manager and/or the manager's board to help them make better decisions. In D2, the key people will be found based on the system's data and information, therefore, the unsupervised machine learning methods can be of better assistance. Here, the cognitive information to be used is related to the people and their roles, tasks, and activities. In D3, the system will still use unsupervised methods to analyze the cognitive information to find the key factors for their later use. Obviously, in this framework, the main part, and the golden stage, is the last stage, which concludes in a system that can help managers to manage more intelligently and, more importantly, more human-focused. Many various machine learning methods and visualization approaches are available to be used. A very simple system can only improve the manager's decision-making by visualizing the cognitive information obtained from previous stages. But also an advanced system can, on its own, be expert, intelligent, smart, semantic, and powered by complex sets of artificial intelligence. This advanced system will use cognitive theories and factors to develop a new generation of organic organization structures and management approaches.

6.2 Ethics and the Human-Centric Analytics

The most current urgent topics related to AI ethics are Privacy, General Ethics, Surveillance, and fairness [49]. The Human-Centric Analytics framework uses data and artificial intelligence technologies, which are two main threats to privacy and general AI ethics. Besides many benefits, this framework can have for organizations and even the whole human community, if it is abused can have disadvantages and ethical problems. Assume this framework can lead to an information system that describes, predicts and analyze people's feelings, behaviour and cognition. There is no need for this analysis to be fully accurate; even with normal accuracy, this analysis can get abused.

These concerns get bigger and more important when using this framework on greater scales, like governments and international policymakers. So, in further studies, the methods and policies of implementing this framework should be investigated from this aspect, and standards should be explained.

7 Conclusion

This paper presents an idea to analyze an organization and then manage it based on that analysis, which is focused on microanalyzing the organization's people. Micro analyzing people means studying their cognitive mechanisms and behaviour when using their mind and brain. To deploy the idea, a framework that involves cognitive science, data science, and the sciences of management and organization is described. While using this framework, any organization can optimize its approaches towards specific goals by having analytics focused on the cognitive properties of people related to that goal. Furthermore, this framework, called Human-Centric Analytics, is very practical for research objectives. Business researchers can study data related to cognition and cognitive psychology to discover the trend and the relationship between organisational behaviour and each person's psychological behaviour. Any society with a goal, regardless of its size, can be considered as an organization, so this framework is advised to be used for any range from governments and governmental organizations for all different purposes to businesses, SMES, and even startups. For developing this framework, the most important subjects and studies that should be considered are: Implementing AI and data science methods on cognitive theories and data sets for analyzing organizations and management, Ethical aspects of developing the framework and using it, Integrating scientific findings in data-driven cognitive psychology in this framework, etc.

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8 Appendix 1: Machine learning algorithms name and abbreviation in figure 3

Abbreviation	**Name**	**Abbreviation**	**Name**
NN	Neural networks	KNN	K-nearest neighbor
NB	Naïve Bayes	SVM	Support vector machine
GA	Genetic algorithms	DT	Decision tree
PCA	Principal component analysis	DDPG	Deep Deterministic Policy Gradient
SARSA	State–action–reward–state–action	NAF	Q-Learning with Normalized Advantage Functions
DQN	Deep Q Network	A3C	Asynchronous Actor-Critic Algorithm
TRPO	Trust Region Policy Optimization	PPO	Proximal Policy Optimization
DNN	Deep neural networks	CNN	Convolutional neural network
RNN	Recurrent neural network	BNN	Binarized Neural Networks