Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Examining Organizational Diagnosis Using Artificial Intelligence: An Empirical Investigation of Small and Medium Enterprises in the UAE

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Organizational Diagnosis (OD) is a process used to collect data regarding how the system is currently operating. Determine the origins of present perspectives by analyzing the data acquired from a modern standpoint. This promotes sustainability and proactive change. On the other hand, machine learning via the artificial Intelligence (AI) lens makes it easier to analyze organizational system knowledge effectively and create the right interventions. Using random selection, two SMEs from the United Arab Emirates were carefully chosen from a pool of 200 individuals. A questionnaire outlining the study's goal and ethical significance was given to the staff. By putting the theoretical components of the study to the test and producing hypotheses to compare with the data, empirical analysis can provide a qualitative understanding of employees' emotions. The findings highlight the application of Artificial Intelligence in computers and support the evaluation of intervention efficacy. The degree to which the intervention meets its goals, the degree to which it is grounded in basic facts, and the ease with which talent may take the place of leadership abilities are all factors in determining its effectiveness. As a result, businesses promote open systems to link behavior to the outside world and other influences.

Keywords: Organizational diagnosis; Digital transformation; Diagnostic model; Open systems; Dialogical Organization Design.

1. Introduction

Organizational Diagnosis (OD) is a dynamic field that adapts to significant change and focuses on complete systems, behavioral insights, and technical consequences. Planning, carrying out, and reinforcing the change are the steps in this process (Cummings et al., 2020). Three categories are covered in an analysis of the patterns that characterize the function and significance of organizational growth. "Changing nature of work" refers to a broad range of organizational evolution and transformation, including the shift from traditional hierarchies and product structures to platform designs (Church & Burke, 2017). Moreover, the dynamic character of data encompasses the diverse aspects of the Internet of Things (IoT) and the necessity for enterprises to be adaptable to manage the amount, speed, and range of data (Riati et al., 2018). Moreover, today's workforce's racial makeup, demography, attitudes, and expectations contribute to "changes in the dynamics of work itself" (Pascoe, 2017).

Artificial Intelligence (AI) is the umbrella term for contemporary analytics, logic-based applications, and technologies that simulate human behavior, decision-making, and processes like learning and problem-solving (Brynlfsson & Mcafee, 2017). For big businesses, it is currently regarded as the most significant and revolutionary new technology (NeVantage, 2019). However, larger businesses are still in their infancy, while smaller firms, except IT companies, are mainly out of reach for these technologies.

According to Worley and Feyerherm (2003), planned change is primarily concerned with the change's internal implementation. Organizations can address issues, adjust to changing conditions, boost output, and shape workplace trends by implementing deliberate change. Only a few theories that outline the many actions a suggested change in a firm can take are implemented by traditional OP methods. This paper outlines a timely procedure that frequently comes before data collection for using OD approaches to enhance organizational change management. Gather information for an analysis that looks at the company, finds issues, and suggests fixes. Moreover, classical open-access methods are based on positivism and open systems (Boucher & Marshak, 2009).

1.1 Purpose of the study

This research will increase organizational effectiveness and streamline the OD analysis process. We will examine the customer's system in greater detail during the scheduled transition period. The analysis process is one of the primary ML procedures. This is selecting the most effective model for comprehending the organization and obtaining, evaluating, and informing management and other stakeholders about issues or opportunities. This research integrates data analysis and artificial Intelligence (AI) to give managers unbiased decision-making information (Jarrahi, 2018). Furthermore, it addresses strategies for implementing projects and organizations that efficiently create a competitive advantage (Liebowitz, 2001). Artificial Intelligence manages expert systems that preserve all organizational experience as a decision-support tool (Tan et al., 2016).

1.2 Objectives

According to surveys, fewer than half of businesses presently engage in extensive AI projects, although that percentage steadily rises (Genpact, 2020). In order to conduct an organizational analysis, pertinent information regarding present operations must be gathered and examined, and judgments about the reasons for performance and areas that may be changed or improved must be made. An organization's performance can be enhanced by identifying information about its systems and planning the necessary actions with the help of practical analysis. Classical OD adheres to positivist principles by using conventional techniques for gathering data. Dialectical machine learning helps businesses break away from the current quo by utilizing various techniques. The analysis assesses the department's overall effectiveness and influence on its constituents. This strategy seeks to pinpoint particular areas where the department's performance needs to improve in the future.

2. Background of the Study and Hypotheses Formulation

Academic and professional groups are conducting business research and information systems (IS) that indicate artificial Intelligence is becoming increasingly prevalent in the industry. The 1950s saw the emergence of artificial Intelligence (AI), initially studied in 1956 at Dartmouth through an interdisciplinary program. To investigate this possibility, the effort brings together scholars from various fields, such as mathematicians, philosophers, and physicists—Artificial Intelligence capable of mimicking human behavior (Benbaya et al., 2020). Artificial Intelligence is becoming increasingly visible in several societal domains, including marketing, healthcare, and human rights. If artificial intelligence application development is not mastered, it can lead to devastating outcomes.

Specifically, Lewin's (1951) change model, action research, proactive models, and dialogic OD change processes are among the theories that become accessible through examining the literature on the nature of planned change. Lewin's model is still helpful in organizational development and can be used to show how organizational models, a different kind of change, can be used (Lippit et al., 1958). Benjamin and Levinson (1993) suggest that the three-stage method serves as a valuable framework for elucidating the optimal utilization of information technology.

In contrast, the second model views planned change as a cyclical process in which the results of early organizational study inspire later activities. The activity's success is then assessed in order to gather fresh data that influences choices made in the future, etc. Members and organizational development professionals collaborate closely in this study and action cycle. Before planning and executing an intervention, a strong focus is placed on gathering and analyzing data and carefully assessing the outcomes (McArdle & Reason, 2008). Action research is frequently intended to support organizations in putting suggested modifications into practice and to offer broader insights that can be applied in different situations (Sussman & Evered, 1978; Schein, 1980; Shani & Bushe, 1987).

A positive role model also draws attention to the organization's advantages. Participants gain a deeper understanding of how their organization operates and learn how to use their strengths for improved outcomes. This upbeat view of transformation aligns with a relatively young area of social science research known as "positive organizational research," which emphasizes the advantages of successful organizations (Cameron et al., 2003). Numerous studies on anticipation effects also corroborate this concept of predicted change (Srivastava, 1990). This demonstrates how people typically act in ways that live up to your expectations. Positive organizational expectations, then, have the power to inspire and direct conduct in order to bring these beliefs to pass. Through a technique known as Appreciative Inquiry (AI), positive models frequently impact suggested improvements (Cooperider, 2017; Al Armoti et al., 2023).

Dialogic change theory, in contrast to Lewin's action research model and methodology, explains the change process. Total OD holds that a society's transformation starts when its members are exposed to a positive image that motivates them to alter their behavior, attitudes, and ways of thinking. Ultimately, this shift in conduct gives rise to fresh presumptions and beliefs that serve as the foundation of culture. It is often acknowledged that culture shapes our thoughts and encourages behavior that varies over time in repetitive cycles (Boucher, 2013). This study puts out the first hypothesis in light of these facts;

H1: AI has a significant role in planned changes towards OD in firms.

Any collection of concepts and connections that describe or explain a system's operation might be called an analytical model. Certain facets of organizational behavior, such as stress among employees, leadership, inspiration, problem-solving, collaboration, work planning, and career development, are frequently the subject of particular studies (Falletta & Combs, 2018). They may also cover the entire organization's environment, strategy, structure, and culture. An analytical model can be built by analyzing aspects or variables connected to organizational effectiveness.

Professionals in machine learning employ conceptual frameworks called analytical models to comprehend organizations. They discuss the organization's efficacy, context, and interactions between various organizational features (Lundberg, 2008). This section comprises some of the most widely used analytical models and describes the systems concept that permeates contemporary OPs. Systems techniques offer a helpful place to start when assessing particular professions, organizations, and groups.

Coordinating unit behavior is the organization's primary goal. It is susceptible to interactions with the outside world and is also impacted by internal variables. Because they are open systems, organizations are structured hierarchically; individual tasks are contained within groups. According to the open systems paradigm, an organization's operations and interactions with its external environment impact the larger ecosystem in which it exists. Businesses gather data and materials from their surroundings and apply them to create ideas, products, and services that incorporate social and technical components. Ultimately, these outcomes are dispersed across the surroundings, and the product's input is forwarded to the company for further activities (Falletta & Combs, 2018).

Moreover, three organizational levels—organizational, collective, and individual—can be used for the analysis. Weisbord's (1976) six-block model, Nadler, and Tushman's (1997) concordance model, Galbraith's (2002) star model, and Kotter's (1978) model of organizational dynamics are a few of the models that have been applied for this purpose. Every level of design highlights how an organization arranges itself within its surroundings. Numerous earlier studies have shown the importance of AI in organizational capabilities (Wade, 2004; Roberts et al., 2012; Lui et al., 2022). However, the development of intermediate capabilities in the context of AI has received less attention (Warner & Wager, 2019; Lui et al., 2022). Because of these drawbacks, the project's second hypothesis is;

H2: AI has a significant role in diagnosing organizational systems.

Long-term sustainable business development is based on knowledge management and business intelligence (Bhatt, 2000; Spender & Grant, 2017). Pandey et al. (2021) and Kim and Park (2017) define collaboration as exchanging information, expertise, and project feedback regarding applications and products to create new technologies and ideas, address issues, and accomplish shared objectives. In an atmosphere with strict regulations, organizations cannot prosper. Therefore, as Tait (2004) notes, risk management, experimentation, and perspective-taking must all be a part of company culture. Some academics developed the idea and framework of AI capabilities, broadened its application, and looked at the influence of AI capabilities on organizational creativity and performance in order to investigate the effect of AI on organizational creativity (Mikalef & Gupta, 2021). Davis (2013) developed a computational creativity system for testing cognitive theories of creativity. Smith et al. (2017) found that creativity can be increased by modeling and coding.

Moreover, as artificial Intelligence is the foundation for advancing and enhancing information exchange, Alansari and Mohamed (2020) and Islam and Assad (2021) stressed the importance of information sharing in helping firms develop a creative culture. It is also a crucial component of social learning, and research has demonstrated that sharing information facilitates the creation of novel concepts, the resolution of problems, and the execution of policies (Cummings, 2004; Sheng & Noe, 2010). Asking about opportunities for information sharing, readiness for sharing, and the impact information sharing has on the success of businesses and organizations is another way to get information from employees. In light of this, the third supposition is;

H3: AI has a significant role in knowledge management and decision-making capability.

3. Research Methodology and Analysis of Data

This study sought to evaluate a hypothesis using a deductive methodology. It also attempts to clarify the relationship between variables and causes and consequences. First, pertinent theories and models were gathered for the investigation based on the suggested modifications and organizational analysis. Three hypotheses were developed to evaluate the relevance level of the latent variables in connection to the dependent variables, information sharing, and decision-making. In order to gather pertinent answers, a closed-ended questionnaire (Table 1) was created and given to staff members of SMEs in the United Arab Emirates. Think about utilizing a stratified sample technique with various responder groups. Initially, a descriptive statistical analysis was carried out to evaluate the validity and reliability of the study's measurements. Subsequently, the study's research model was tested by assessing the path coefficients of the essential variables' contributions and importance. SPSS 24.0 was used to examine a subset of the replies. Furthermore, goodness-of-fit tests assess how healthy theories match the data quantitatively. Various criteria are involved in predicting the factor structure/testing model, including identifying the test items (indicators) that influence each factor; that is, these factors should have high or moderate loadings (or beta coefficients). SEM practitioners have attempted to create dispersed or alternate adaptation measures to address these issues and complications. They have to specify the level of approximation and the discrepancy between the estimates and offer more justification for adopting or rejecting the model (Proudhon, 2015). As a result, relationships between external (independent) and endogenous (dependent) factors can be studied concurrently. The structural model was added to the measurement model in the subsequent estimating step after the measurement model was initially estimated in a two-stage analysis. The justification for this strategy is that it is preferable to illustrate indicators' reliability precisely in a two-step procedure by avoiding the interaction of construct and measurement models. Tests for statistical significance and substantive validity of the estimates, convergence of the estimating process, empirical refinement of the model, statistical significance of the variables, and goodness-of-fit are used to determine the model's goodness-of-fit, according to a standard technique. 0.05 was used as the significance threshold. According to Kenny (2012), the CFI and TLI are artificially high in cases with a higher correlation between the variables, indicating a better fit.

Table 1. Measures for latent variables

Latent Variables	Related Factors
Planned change	Q1. My firm measures its efforts with its objectives.
	Q2. I use the organization's core values with my knowledge, skills, & abilities.
	Q3. My firm tries to find problems and find a solution for it.
	Q4. My firm develops advanced approaches to emerging needs. Q5. My organization ensures that the work group or team undertakes appropriate planning activities.
	Q6. My firm analyses the workgroups that undertake planning activities.
Organizational diagnosis	Q7. My firm is keen on business problems and implementing AI initiatives to solve them.
	Q8. My firm can anticipate and plan for risks.
	Q9. My firm's managers have good knowledge of applying AI.
	Q10. My firm involves all stakeholders in decision-making.
	Q11. My firm provides access to large and fast-moving data for analysis.
	Q12. My firm integrates external data with internal data to enhance the high-value analysis of our business settings.
	Q13. My firm can provide all relevant data at the right level of graininess to produce meaningful insights.
Knowledge management and decision-making	Q14. My firm allows me to exchange my knowledge and ideas.
	Q15. My firm's AI strategies are aligned with the organization's mission.
	Q16. My firm has good leadership to support and fund AI initiatives.
	Q17. Do you feel self-confident in assigning your tasks with AI?
	Q18. My firm provides rewards for my knowledge, skills, and abilities.
	Q19. My firm has a positive culture of learning and development.
	Q20. I feel my company values my ideas at work.

A five-point scale from 1 ('strongly disagree') to 5 ('strongly agree') was used for 23 indicator surveys related to two latent variables to the dependent variable, knowledge management and decision-making (Bergmann et al., 1999).

4. Data Analysis

Table 2. Descriptive Statistics and Correlation Matrix for Planned Changes, OD, and KM & DM Variables

	N	Average	Std. Deviation	1	2	3	4
Planned changes	112	3.2857	0.752	1			
OD	112	4.4286	0.743	0.723**	1		
KM & DM	112	3.6161	1.242	0.611**	0.501**	1	
Valid N (listwise)	112						
*p<0.05 **p<0.01							

The table offers structural analysis, change ideas, and descriptive statistics on latent variables for information management and decision-making. Since questions 1 through 6 are related to personal computers, each person receives a total score of 30. The relationship between planned changes and OD is positive (0.723, $p<0.01$), while the relationship between OD and computer driving information is positive (0.501, $p<0.01$).

Given that questions 7 through 13 deal with organizational analysis, each subject has a total score of 35 points, with a mean score of 4.42 points and a standard deviation of 0.74 points.

The knowledge management activities covered by questions 14 through 20 resulted in a total score of 35 points for each individual, with a mean score of 3.61 and a standard deviation of 1.24.

a. Correlation Analysis

Table 3. Pearson Correlation Matrix for Planned Changes, O. Diagnosis, and KM & DM Variables

		PC	OD	KM & DM
Planned changes	Pearson Correlation	1	.979**	.960**
	Sig. (2-tailed)		.000	.000
	N	112	112	112
O. Diagnosis	Pearson Correlation	.979**	1	.983**
	Sig. (2-tailed)	.000		.000
	N	112	112	112
KM & DM	Pearson Correlation	.960**	.983**	1
	Sig. (2-tailed)	.000	.000	
	N	112	112	112
**. Correlation is significant at the 0.01 level (2-tailed).				

The analysis above explains the relationship between the three factors. Every factor exhibits a robust association with the others. Planned changes and knowledge-sharing are associated with organizational diagnosis 96% and 98% of the time. Also, there is a 98% association between OD and KS. There is a strong correlation between each correlation.

Regression Analysis

Planned change is taken as a dependent variable, and organizational diagnosis is taken as an independent variable.

Table 4. Regression Coefficients for the Relationship between Organization Diagnosis and the Dependent Variable

	Unstandardized Coefficients		Coefficients	t	Sig	95% Confidence Interval for B	
	B	Std.Error	Beta			Lower Bound	Upper Bound
Constant	-1.084	0.386		-2.811	0.006	-1.848	-0.320
Organization diagnosis	0.819	0.016	0.979	50.78	0.000	0.787	0.851

The table confirms the values: Organization diagnosis = 0.819 (planned changes) -1.084 and (R^2 = 0.98). This indicates there is a significant positive relationship between the two variables.

Regression

The next part tries to find the Organization diagnosis as the dependent variable and knowledge management as the independent variable.

Table 5. Regression Coefficients for the Relationship between Knowledge Management and the Dependent Variable

	Unstandardized Coefficients		Coefficients	t	Sig	95% Confidence Interval for B	
	B	Std.Error	Beta			Lower Bound	Upper Bound
Constant	-4.493	0.629		-7.139	0.000	-5.740	-3.246
Knowledge management	0.885	0.024	0.960	36.18	0.000	0.836	0.933

In the table, the value of knowledge management is 0.885 to (OD) - 4.493 and (R^2 = 0.96). The beta value of 0.96 indicates a positive association.

Organizational diagnosis is the dependent variable in a regression analysis, with projected modifications as the independent variable.

Table 6. Regression Coefficients for the Relationship between Planned Changes and the Dependent Variable

	Unstandardized Coefficients		Coefficients	t	Sig	95% Confidence Interval for B	
	B	Std.Error	Beta			Lower Bound	Upper Bound
Constant	2.187	0.429		5.093	0.006	1.336	3.038
Planned changes	1.171	0.023	0.979	50.78	0.000	1.125	1.217

The value shows for Organization diagnosis = 1.171 and (Planned changes) +2.187. The R^2 = 0.979.

Regression for organizational diagnosis is the dependent variable, and knowledge-sharing is the independent variable.

Table 7. Unstandardized Regression Coefficients and Related Statistics

	Unstandardized Coefficients		Coefficients	t	Sig	95% Confidence Interval for B	
	B	Std.Error	Beta			Lower Bound	Upper Bound
Constant	-4.224	0.496		-8.515	0.000	-5.207	-3.241
Knowledge-sharing	1.083	0.019	0.983	56.166	0.000	1.045	1.121

The table indicates the organizational diagnosis = 1.083 AND (KS&DM) - 4.224. Also, the R^2 = 0.983.

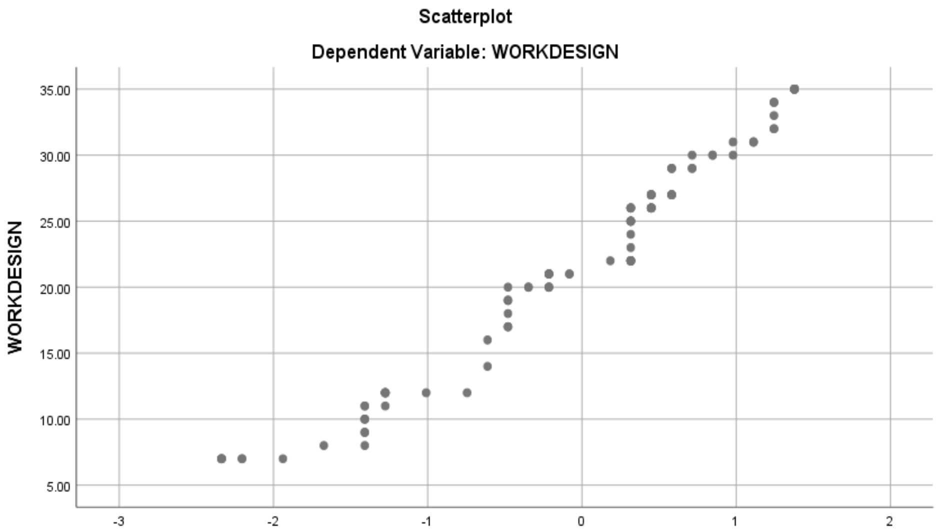

Figure 1. Regression Standardized Predicted Value

Regression: Knowledge-sharing is considered the dependent variable, and planned changes are an independent variable

Table 8. Unstandardized Regression Coefficients and Related Statistics

	Unstandardized Coefficients		Coefficients		t	Sig	95% Confidence Interval for B	
	B	Std.Error	Beta				Lower Bound	Upper Bound
Constant	6.593	0.537			12.288	0.000	5.529	7.656
Planned changes	1.043	0.029	0.960		36.180	0.000	0.986	1.100

Knowledge-sharing = 1.043 (Planned changes) + 6.593 ($R^2 = 0.955$)

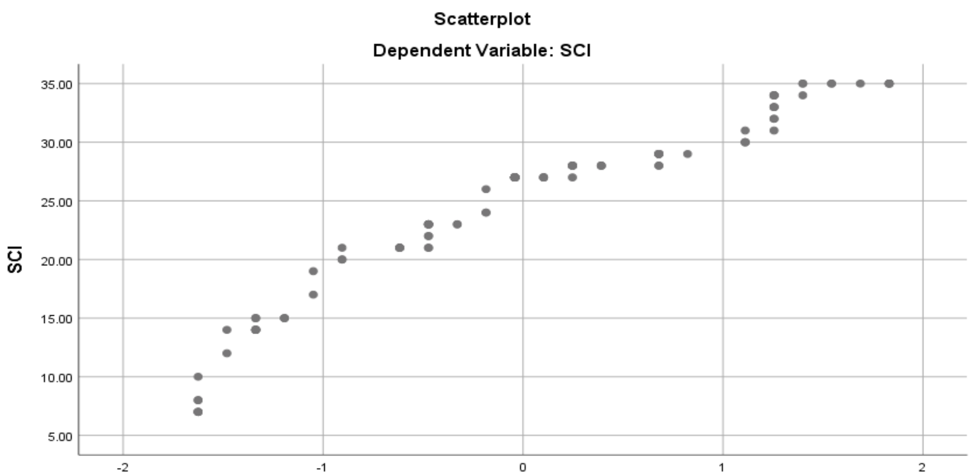

Figure 2. Regression Standardized Predicted Value

Regression: Knowledge-sharing is judged as the dependent variable, and organizational diagnosis is the independent variable.

Table 9. Unstandardized Regression Coefficients and Related Statistics

	Unstandardized Coefficients		Coefficients	t	Sig	95% Confidence Interval for B	
	B	Std.Error	Beta			Lower Bound	Upper Bound
Constant	4.599	0.380		12.109	0.000	3.847	5.352
Organizational diagnosis	0.892	0.016	0.983	56.166	0.000	0.861	0.924

Knowledge-sharing = 0.892 () +4.599 (R^2 = 0.989)

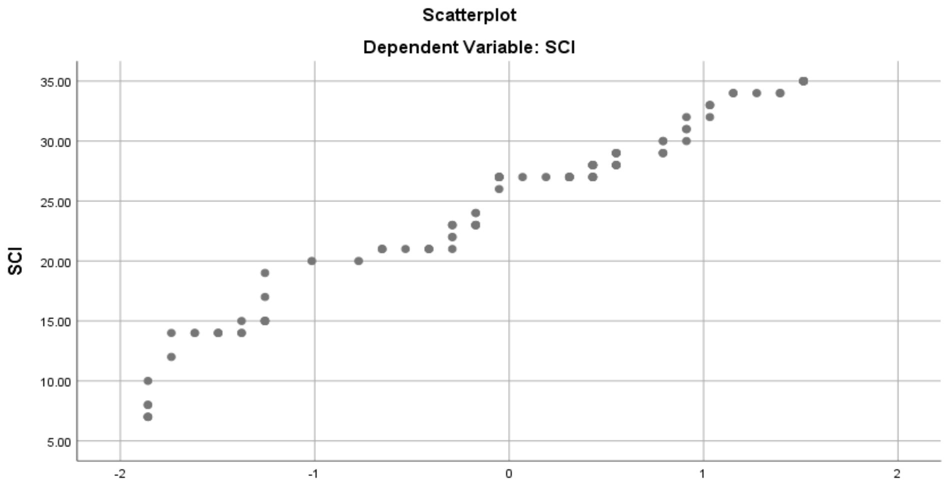

Figure 3. Regression Standardized Predicted Value

5. Discussion on theoretical and practical implications

This article develops a study model on the influence of artificial Intelligence on planned changes in firms based on a conceptual model of organizational analysis. These findings bolster the notion that organizational analysis, information management, planned change, and decision-making are positively correlated. The paper first discusses planned change, the models that go along with it, and how AI may support organizational change. The study's findings demonstrate that several theories discussed in the literature can be used to include artificial Intelligence in the suggested modifications. This incites modifying procedures, structures, and policies to enhance organizational performance. These theories connect organizational activities and action plans through problem identification, data gathering, analysis, feedback, etc. They outline an organization's standard processes to accomplish change and the organizational development activities required to bring about that change. Though the suggested change model only covers the last phases of the open access process development, there are several changes based on the circumstances. The suggested changes will be affected differently depending on the extent of the changes, how the customer's systems are organized, and whether the environment is domestic or foreign. The suggested modifications differ significantly if the pertinent circumstances are different. (Sussman and Evered, 1978; Cameron et al., 2003; McArdle and Reason, 2008; Cooperrider, 2017; Shane, 1980; Shani and Boucher, 1987; Levine, 1951).

This research delves into the connection between tissue analysis and artificial Intelligence. PE and nonprofit professionals must know what data must be gathered and examined to analyze an organization. The organizational structure always plays a role in determining what to look for. These theories cover a broad spectrum, from scientific to intuitive accounts of organizations' functions. Misdiagnosis can result from focusing on specific qualities, frequently at the expense of other characteristics. For instance, an analytical model that connects interpersonal conflict management to team success would motivate OD practitioners to look at member relationships, decision-making procedures, and conflict-resolution techniques. These topics are pertinent, but they neglect other team concerns, such as members' abilities and expertise, the difficulty of the team's work as a unit, and the interdependence of duties. As a result, this research enables the identification and selection of analytical models and methodologies to guarantee rigor and address inquiries made by the company (Weisbord, 1976; Galbraith, 2002; Roberts et al., 2012; Lui et al., 2022).

Thirdly, the findings demonstrate that the analysis is grounded in a conceptual framework of the organization's operations and functions as a roadmap, prioritizing areas that need to be scrutinized from the standpoint of unit management. Research results highlight the value of ideas, information, criticism, and shared objectives inside organizations (Pandey et al., 2021; Kim & Park, 2017). These topics are pertinent, but they neglect other team concerns, such as members' abilities and expertise, the difficulty of the team's work as a unit, and the interdependence of duties. As a result, this research enables the identification and selection of analytical models and methodologies to guarantee rigor and address inquiries made by the company (Weisbord, 1976; Galbraith, 2002; Roberts et al., 2012; Lui et al., 2022).

Thirdly, the findings demonstrate that the analysis is grounded in a conceptual framework of the organization's operations and functions as a roadmap, prioritizing areas that need to be scrutinized from the standpoint of unit management. Research results highlight the value of ideas, information, criticism, and shared objectives inside organizations. As Thite (2004) noted, more than tightly regulated environments are needed to develop creativity and innovation. Organizational architecture must promote innovation, risk-taking, and the ability of knowledge workers to envision novel outcomes. Thus, this study demonstrates that businesses must encourage and invest in knowledge workers and structures to thrive and remain competitive in the information era. Businesses can stay competitive in the future by identifying and planning for change with the use of AI techniques.

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