Using psychological networks to develop an integrated relational framework to understand organizational climate

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Abstract

This study presents an integrated relational framework for investigating and comprehending organizational climate using the interactive dimensions of Quinn and Rohrbaugh's Competing Values Model (CVM). With a survey of 1,053,118 workers from 156 Brazilian companies and the application of a psychological networks technique, this research identified five distinct clusters from the vicinity of the most central nodes, offering further insights into the interactions between different CVM domains. Using the clusters within the four CVM quadrants, a Relational Framework for Organizational Climate was developed, providing an integrated approach that displays the most relevant item connections from various dimensions, aiding in the understanding of organizational climate. Among the various findings, this study emphasizes the centrality of enabling workers to participate in decision-making processes as the inter- and intra-organizational aspect most critical to the understanding and improvement of organizational climate. This study also considers additional issues in the context of the contributions of utilizing psychological networks for researching organizational climate, providing insights for further development.

Keywords: organizational climate; competing values model; psychological networks; relational framework, HRM

Employing Psychological Networks to develop an Integrated Relational Framework for Organizational Climate

Introduction

Organizational climate (OC) is a critical area of study in organizational psychology, as it plays a central role in identifying and understanding the regulatory and guiding factors that shape human behavior within organizational contexts (Schneider, 2021; Schneider, Ehrhart, & Macey, 2013; Woznyj, Heggestad, Kennerly & Yap, 2019). Despite being a multifaceted construct, there is no consensus on the number of dimensions necessary for accurately measuring organizational climate. Previous studies have offered a limited focus on organizational climate strength, despite earlier recommendations (e.g., Sora et al., 2013). Scholars have proposed anywhere from four (Campbell et al., 1970) to fifty-four dimensions (Koys & DeCottis, 1991) for assessing organizational climate. Similarly, in industry reports, organizations may choose which dimensions to investigate for their annual organizational climate research, based on the degree to which they align with their business strategies and the information they seek to elicit from employees (Ćulibrk et al., 2018; Mulki & Lassk, 2019).

Patterson et al. (2005) developed a widely used framework for measuring organizational climate and employee satisfaction, based on Quinn and Rohrbaugh's (1981) Competing Values Model (CVM). Originally designed to identify the key indicators of effective organizations, the framework was developed by analyzing studies conducted between 1960 and 2000. The authors sought to create a new instrument to measure organizational climate using the CVM, resulting in a measure that places various dimensions into one of the four approaches (quadrants) of the CVM. These include: a) Human Relations Model (employee welfare, autonomy, participation, communication, training, integration, and supervisory support), b) Internal Process Model (formalization and tradition), c) Open

Systems (flexibility, innovation, outward focus, and reflexivity), and d) Rational Goal Model (clarity of organizational goals, effort, efficiency, quality, pressure to produce and performance feedback).

Patterson et al. (2005) assert that utilizing the Competing Values Model (CVM) for research on organizational climate offers several benefits in addressing conceptual and methodological issues related to its measurement. By placing emphasis on the competing values within each of the four quadrants (Human Relations Model, Open Systems Model, Internal Process Model, and Rational Goal Model), the CVM provides a more comprehensive and multidimensional framework for HRM professionals and academics to better understand organizational climate. Furthermore, the complexity of determining how different competing values interact and what emphasis should be placed on each quadrant is also a significant factor impacting the measurement of organizational climate. In other words, the interrelations among the factors from different models and how they may influence one another is a crucial element that can be used in order to better explain the integrated and complex nature of organizational climate.

This research thus extends the study conducted by Patterson et al. (2005) by using it as an overarching model to develop a framework for investigating organizational climate based on the interaction of the different CVM dimensions. To develop this framework, named the Relational Framework for Organizational Climate (RFOC), we applied psychological networks, a novel technique to the field of organizational psychology and HRM, to model the complex relationships underlying items from different dimensions of organizational climate. One of the main advantages of using psychological networks is that it allows all variables to freely interact with one another, forming not only an integrated set of networks as proposed by Patterson et al. but also a causally connected system (Borsboom, 2008). For this study, data from more than one million workers from companies based in

Brazil were analyzed, and measurement equivalence tests were conducted to ensure the study's replicability.

This study presents a relational framework that HRM scholars can use to understand the complex interactions within organizational climate. This framework builds on the work of Paterson et al. and provides firms with a better understanding of how different elements of organizational climate relate to one another. From a practical standpoint, the research offers HR managers a new set of tools to measure the integrated and relational aspects of organizational climate and identify key characteristics that are likely to impact it.

A network approach to organizational psychology

The concept of psychological networks has its roots in the study of particle orientation by Lenz and Ising, which gave rise to the Ising Network Model (Brush, 1967). In recent years, networks have been viewed as interconnected elements reinforced by associations (Marsman et al., 2018; Menezes et al., 2019; van der Maas et al., 2006), providing a better understanding of how complex interactions among psychological variables occur (Epskamp, Borsboom & Fried, 2018; Letina, et al., 2019). Psychological networks are distinct from latent causal models, such as unidimensional item response theory and structural equation modelling, in that they do not model the dependencies among observable variables (Borsboom, 2008; Menezes et al., 2019). Rather than seeking a common cause representation of psychological variables by creating separate dimensions for different aspects, such as role clarity and communication, psychological networks explore the interactions between elements of these dimensions as a single entity.

To construct and understand a psychological network, two components are required: *nodes*, which represent observable behaviors or items in a psychological assessment, and *edges*, which denote the associations among them. From a statistical perspective, nodes correspond to main effects, whereas edges correspond to pairwise interactions (Marsman et al., 2018). When applied in the context of organizational psychology research, psychological networks can create an interconnected system of reinforcing organizational behaviors that reveals how different variables interact with each other. This approach highlights which variables are more central to explaining participants' psychological traits, and thus showcases its strengths, as suggested by Sora et al. (2013). Despite the prevalent use of non-experimental designs in organizational psychology research, psychological networks can provide potential interconnected pathways that help HR professionals and academics deepen their understanding of the underlying relationships (Epskamp, Borsboom & Fried, 2018; Schneider, 2021). For example, if workers do not rely on their organization's leadership, it can adversely affect team morale and ultimately increase turnover intentions. This structure not only indicates the interconnectedness between different factors and potential outcomes but also helps to predict turnover intentions by knowing the staff's attitudes towards leadership and their intention to leave the organization (Bakker, Albrecht & Leiter, 2011; Konrad, 2000). However, it is also possible to predict turnover intentions from team morale, which makes individual members' attitudes towards leadership less important in predicting turnover intentions. Accordingly, the correlation between leadership and turnover intentions is estimated to be zero, making these two variables conditionally independent from each other.

The property of partial correlation can be applied to all relationships among items in a network. Partial correlation coefficients are used when data is assumed to be continuous or ordinal. Partial correlation networks are a type of undirected network, specifically a Markov random field, in which edges are solid lines with no arrows, indicating that the edge (x, y) is the same as the edge (y, x). This results in a smaller number of nodes and edges that are more recognizable and analyzable, making it easier to identify highly interconnected clusters or nodes. Community detection algorithms such as those developed by Briganti et al. (2018) and Hoffman et al. (2018) can also aid in this process. Clustered nodes are considered enclosed variables through which critical worker and workplace information can be analyzed, as noted by Costantini et al. (2015) and Dalege, Borsboom, van Harreveld, and van der Maas (2017).

Techniques such as walktrap are useful for recognizing and analyzing organizational community issues, especially in large workplace networks with over 1000 nodes (Yang, Algesheimer & Tessone, 2016). Walktrap algorithms use random walks to identify structural similarity between nodes within communities, which can highlight weak and strong associations in the network (Pons & Latapy, 2005).

Estimation of Psychological Networks

The final step involved in estimating psychological networks concerns the predictability of the nodes. This refers to how much of the variance of a node can be predicted by the edges connected to it (Haslbeck & Waldorp, 2018; Letina et al., 2019). Such analysis can add weight to the edges and provide information about interactions between variables from different dimensions that would not be revealed by traditional data analysis methods. The importance of nodes, or how influential they may be in a network, can be assessed via centrality indices of the network structure (Costantini et al., 2015; Newman, 2010; Opsahl, Agneessens & Skvoretz, 2010). The three main measures of centrality are *strength*, which reflects how well a node is directly connected to other nodes, *closeness*, which shows how well a node is indirectly connected to other nodes, and *betweenness*, which quantifies the number of times a node acts as a bridge along the shortest path between two other nodes (Epskamp et al., 2018).

Recent studies conducted by Epskamp et al. (2017) and Epskamp, Borsboom & Fried (2018) have shown that strength is the most reliable centrality index when cases are removed from the data set, while betweenness and closeness are not estimated accurately. Centrality measures are typically presented as standardized z-scores in most statistical packages, and the interpretation is straightforward, with higher scores indicating greater node centrality and lower scores indicating less central nodes. For cross-sectional network models using small sample sizes, Epskamp et al. (2018) recommend computing the stability of centrality indices and the accuracy of edge weights. However, since this investigation uses a large dataset, these estimates are considered irrelevant for this study. For more information on how to calculate these measures, refer to Menezes et al. (2019).

Psychological networks as a research technique are still in their early stages, but they have proven to be an invaluable tool for gaining insights into the associations among various organizational variables. These insights provide useful information for modelling the multidimensional effects of relationships on organizational climate. The research in this area uses the framework proposed by Patterson et al. (2005) as an overarching model to assess the most relevant connections observed using psychological network methods to model the relationships between different CVM dimensions and organizational climate.

Methods

Procedures and demographics

The study collected data through surveys conducted by a global management firm that specializes in consulting services related to organizational climate research. The firm collected data from several independent studies conducted between 2014 and 2018, and the resulting dataset comprised responses from 1,053,118 workers from 156 companies based in Brazil, including some of the country's largest companies. The sample included 16.3% of workers from retail companies, 14.9% from the steel industry, and 12.0% from the food and beverage industry, with the remaining participants representing other sectors. The majority of respondents were male (61.3%), born between 1980 and 2000 (52.4%), and working in nonmanagerial positions (87.9%). In terms of length of employment, 33.6% of respondents had worked for up to two years in their organizations, while others had worked for over 10 years. The highest level of education reported by respondents was high school (36.4%), followed by university degrees (30.8%).

Measurements and Instruments

For this study, a total of 38 items were selected from an initial pool of 418 items designed to measure various dimensions of organizational climate. In order to encompass all dimensions within the Competing Values Model, two items were selected for each dimension, as explained in more detail below. All items were designed to reflect positively on the assessed aspects, and no reverse scoring was employed. Participants were asked to respond on a five-point Likert scale, with 1 indicating strong disagreement and 5 indicating strong agreement.

Due to copyright restrictions, the actual items used for this investigation cannot be shown. Instead, a summary of the central ideas underlying each item is presented below:

a) Human Relations Model

Employee welfare: Welfare.1 - The company has a genuine interest in the welfare of its employees, and 2) Welfare.2 – Feeling of being valued at work.

Autonomy: Auto.1 - Enough autonomy to carry out work effectively, and Auto.2 - Freedom of expression in the workplace.

Participation: Particip.1 - Participation in goal setting with immediate superior, and Particip.2 - Participation in decision-making relating to processes that fall under the individual’s responsibility.

Communication: Commun.1 - Employees are informed about decisions and changes in the company, and Commun.2 - Communication flows openly within the organization.

Training: Training.1 - Opportunity to develop knowledge, skills and competences, and Training.2 - Training programs offered by the company meet individual development needs.

Integration: Integrat.1 – There is cooperation between different areas of the company, and Integrat.2 - company's activities between different areas are coordinated and integrated.

Supervisory support: SSupport.1 - Immediate superior is accessible/available when needed, and SSupport.2 - Immediate superior provides the necessary conditions for the fulfillment of responsibilities assigned to subordinates.

b) Internal Process Model

Formalization: Formaliz.1 - Company's processes and working practices are clear and standardized for the achievement of results, and Formaliz.2 - Workflow is well organized.

Tradition: Tradit.1 - The company has a strong culture of development, and Tradit.2 – Individual identification with company values.

c) Open Systems Model

Flexibility: Flexib.1 - Company is up to date with changes in the external environment (competitors, economy, market, technology, etc.), and Flexib.2 - The company responds effectively to changes in the business environment (market, competitors, technologies, economy, etc.).

Innovation: Innovat.1 - The company seeks and encourages innovation, and Innovat.2 - Good ideas / suggestions from employees are put into practice.

Outward focus: OutFocus.1 - The company has a customer focus, and OutFocus.2 - The company meets the needs and demands of its customers.

Reflexivity: Reflex.1 - Work processes are well-planned, and Reflex.2 - The company adapts its operational methods in order to improve work efficiency.

d) Rational Goal Model

Clarity of organizational goals: ClarGoal.1 - Clear communication of the company's business strategies and goals, and ClarGoal.2 - My area has well defined work goals.

Effort: Effort.1 - The company motivates me to do my best, and Effort.2 - I am encouraged to take calculated risks in order to boost the company's results.

Efficiency: Efficiency.1 - The company has defined criteria for evaluating employees' performance, and Efficiency.2 - The company expects a high level of performance from its employees.

Quality: Quality.1 - The company seeks to improve the quality of its products and services, and Quality.2 - People in my area are committed to delivering quality products and services.

Pressure to produce: Pressure.1 - The pressure I have to do my work is adequate, and Pressure.2 - In our team we have high demands regarding the efficiency and quality of our work.

Performance feedback: PerfFeed.1 - I am familiar with the criteria used to evaluate my individual performance, and PerfFeed.2 - I receive sufficient feedback on the quality of my work.

Data Collection and procedures

The item bank used in this investigation was created based on the emerging needs of clients. Specifically, different sets of items were administered in various organizations based on the nature of their businesses. For example, if a company did not have policies related to “social responsibility” because their activities were not believed to have a direct environmental impact, then environmental items were not included for that organization.

After selecting a defined set of items for administration in a company, participants were invited to take part in the survey using the company's corporate email, which was linked to the consulting company's website to ensure compliance with confidentiality and data protection policies. All participants were provided with an Informed Consent Statement, and the confidentiality of data storage and processing was both assured and agreed upon.

To facilitate this process, individuals' personal information was stored and used as non-personally identifiable information (non-PII), thereby ensuring that tracing and/or identification of personal information could not be done either directly or indirectly.

Data Analysis

Due to the complexity of handling a large-scale dataset that includes hundreds of items, three initial studies were carried out to select the items that were most appropriate for this investigation. These studies consisted of: 1) Content validity, 2) Missing data, and 3) Construct validity.

Content validity

To assess the quality of each item individually, a panel of subject-matter experts consisting of four members with expertise in organizational climate was assembled. This procedure plays a crucial role in providing incremental validity (Mastaglia, Toye, & Kristjanson, 2003; Spengler, Gelléri, & Schuler, 2009). After conducting a rigorous process of content analysis for each of the 418 items, the panel decided to remove several items based on the following criteria: two items were deemed redundant and carried multiple ideas simultaneously, forty-one items were considered too lengthy and had content that was too difficult to understand by all respondents, fifty-three items had content that was not applicable to all conditions and organizations (e.g., items that involved the application of total quality management tools or variable remuneration), twenty items were flagged as repetitive and covered similar content or ideas introduced by other items, and thirteen items were excluded due to significant disagreements among experts concerning their overall quality. In total, 122 items were excluded due to content validity-related issues.

Missing data

Since different sets of items were administered to the participating workers in the study, no respondents were exposed to all 418 items, resulting in non-ignorable nonresponse, also known as missing data not at random (MNAR). Consequently, the planned missingness design could not implement listwise deletion as it would necessitate complete cases in the dataset. Thus, all the descriptive data statistics were calculated using pairwise deletion. Moreover, as construct validity techniques and network psychometrics can handle missing data, the complete dataset was used for the data analyses.

To eliminate items with a large number of missing cases, particularly those that were administered in just a few companies, only items with less than 99% missing responses were initially selected. Consequently, 151 items were excluded from the analysis, as they had fewer than 10,531 valid responses.

Construct validity

To investigate whether the items were aligned with their intended dimensions, the Graded Response Model (GRM) by Muraki and Carlson (1995) was employed to compute the psychometric parameters for each dimension separately. Using Item Response Theory (IRT), such as GRM, allows for the identification of an individual's response pattern rather than the structure of the correlational multivariate distribution of responses (Wirth & Edwards, 2007). Since the items are typically strongly correlated with their respective dimensions, three criteria were used for selecting the most psychometrically sound items: (a) factor loadings ≥ 0.7, (b) item discrimination ≥ 1.7, and (c) item information function ≥ 4.0, representing an information proportion of approximately 80%. A total of 29 items were excluded for not meeting these criteria. Additionally, 10 pairs of items measuring the *Leadership* dimension had correlations above 0.80, indicating potential redundancy. After reviewing the content of these combinations, three pairs were identified as having very similar content and were excluded.

The final item bank included 148 items covering different aspects of organizational climate, with 38 items matching the dimensions of the Competing Values Model ultimately selected. To balance the dimensions and control for potential biases toward a specific dimension, two items were chosen for each dimension.

To enhance the study's replicability, a cross-validation approach was used, with 50% of the complete dataset cases randomly assigned to a training set and the remaining 50% to a testing set. The resulting two networks each comprised 789,838 data cases, and a high-performing computer was used to estimate the Gaussian Graphical Model (GGM) regularized with LASSO. However, since LASSO estimation penalizes near-zero edges, the interpretation of regularized partial correlations is not the same as traditional correlation coefficients. Thus, edges with stronger associations were considered most critical. For the identification of clusters of nodes densely connected, the walktrap algorithm was used for community identification.

As the R packages *qgraph* and *bootnet* used for network estimation do not permit out-of-sample comparisons, a multiple-group confirmatory factor analysis (CFA) model was fitted to assess measurement invariance between the training and testing datasets. Measurement invariance examines whether the same attribute is being assessed across comparison groups (Hallquist, Wright, & Molenaar, 2019). If the parameter estimates are equivalent for both datasets, it is likely that the findings can be replicated in other samples, provided that the same conditions remain unchanged (e.g., item set, rating scale, administration mode, etc.). Since the same measurement method was employed for all participants, splitting the dataset into two parts can also aid in controlling for common-method bias (Podsakoff et al., 2003). This is because participants were surveyed in different years, responded to different item blocks, and belonged to distinct organizations.

Results

The interpretation of complex networks presents challenges due to the large number of associations among the nodes, which can make it difficult to visualize spatial pattern formation. For example, when estimating an organizational climate network consisting of 38 items, a total of 741 parameters are calculated using the equation p + [p * (p-1)/2], where p is the number of nodes (Costantini et al., 2015). To address this challenge, the walktrap community identification algorithm was deployed to provide insights into the relationships among the nodes and how they might form sub-graphs (Sousa & Zhao, 2014). For both training and testing datasets, a single community was detected, indicating that the random walk distances among nodes are too short to create separate communities. This finding may suggest that the construct of organizational climate is so dense that subgraphs cannot be identified using a community detection approach, underscoring the need to investigate more specific interactions between items. Overall, the association patterns among nodes in both networks are quite similar, as depicted in Figure 1.

Insert Figure 1 about here

Similar patterns were observed for both the training and testing datasets in terms of the centrality of the variables. Specifically, the most and least central variables were rated similarly when ranked by Strength, while more variations occurred around the midpoint of the scale. Centrality plots for each network are presented in Figure 2. The Strength metric (x-axis) can be interpreted as a z-score, where a score of zero represents the mean. Only variables that contribute positively to the network are expected to provide meaningful information for explaining organizational climate. Conversely, nodes with Strength values below zero have fewer connections with other nodes and are less influential in the network as a whole.

Insert Figure 2 about here

Although only a single community was detected, further analysis of the network revealed the formation of five smaller clusters when comparing the most central items sorted by Strength with their position in the network. Some variables participated in more than one cluster, which provided additional insights into the interrelationships among the different dimensions of the Competing Values Model and how their elements integrated to form the Relational Framework for Organizational Climate proposed by this study.

Cluster 1

The first cluster identified in the network analysis was dominated by the item with the highest centrality in the training dataset and the third-highest centrality in the testing dataset, which pertains to individuals' involvement in organizational decision-making related to their responsibilities (Particip.2). The mutual interactions between Particip.2 and other highly correlated items in the cluster suggest that organizational identification and the degree of autonomy granted to employees are key drivers of perceptions of organizational climate. This is evident from the strong connections established between Particip.2 and items such as Auto.1 ($r = 0.32$), Welfare.2 ($r = 0.30$), and Tradit.2 ($r = 0.33$). Thus, this cluster indicates that a high level of autonomy and improved participation in decision-making processes that affect workers could foster their sense of belonging and perception of being valued at work, consistent with previous research (Randell et al., 2018). In other words, the first set of interactive features that may impact organizational climate involve the extent to which workers perceive their level of participation in organizational life and how this relates to and influences both their sense of identification and well-being.

Conversely, the cluster has also exposed negative associations between identification and autonomy with customer orientation ($r = -0.31$, OutFocus.1), adequate feedback provision on the quality of work ($r = -0.28$, PerfFeed.2), and the company's effectiveness in responding to changes in the business environment ($r = -0.28$, Flexib.2). As a result, perceptions of autonomy and organizational identification diminish when workers receive increased feedback on their job performance and when the organization's focus shifts from internal affairs to external factors for fulfilling customer demands and adapting to critical changes.

Cluster 2

The second cluster highlights the significance of stakeholders perceiving work processes as well-planned (Reflex.1), which is directly related to effective communication of decisions and changes across the company ($r=0.32$, Commun.1), and the level of autonomy granted to employees for carrying out work efficiently ($r=0.24$, Auto.1), which was also part of the first cluster. Furthermore, Reflex.1 is positively correlated with the extent to which the organization encourages employees to give their best ($r=0.25$, Effort.1). Conversely, there is a negative correlation between Reflex.1 and Formaliz.2 ($r=-0.33$), suggesting that a poorly planned work process may require better organization of workflow. The pattern of relationships between the items in this cluster indicates some typical elements of transformational leadership, as the more workers realize that their superiors are concerned with streamlining organizational processes, sharing important information at work, and providing autonomy and resources to accomplish their goals, the more motivated they become to perform their best (Han, Seo, Yoon & Yoon, 2016; Hetland, Hetland, Bakker & Demerouti, 2018).

Cluster 3

The third cluster integrates various factors that highlight the significance of performance management to organizational climate, with particular emphasis on the immediate superior's role in the process. The central node addresses the extent to which workers are informed about the criteria used by the company to evaluate their individual performance (PerfFeed.1). This requires active participation from immediate superiors, whose responsibilities involve setting goals and establishing clear performance expectations with employees (r=0.39, Particip.1), providing adequate feedback on the quality of individual work (r=0.31, PerfFeed.2), and being available to workers when needed (r=0.35, SSupport.1). Furthermore, this cluster may also be influenced by the perception of organizational justice, although this dimension is not included in Patterson's model. Explicit and well-communicated criteria for evaluating performance relate to the dimensions of informational, procedural, and interpersonal justice at various levels (Greenberg, 2011). Conversely, when workers become more familiar with the criteria used in their performance appraisal, they may believe that their leaders have failed to define these criteria (r=-0.34, Efficiency.1), increasing pressure on how they handle their duties and responsibilities (r=-0.30, Pressure.1). While the focus of this cluster primarily revolves around performance management, given the high centrality of PerfFeed.1, some notable features of transformational leadership are also evident, as in the previous cluster. Failing to define performance criteria is therefore inconsistent with organizational justice and represents an additional burden or demand on employees, ultimately draining their performance capability (Bakker & Demerouti, 2017).

Cluster 4

The fourth cluster relates to the company's external focus, more appropriately termed as customer orientation. The most central item in this cluster is the perception of workers that their companies are capable of meeting the needs and demands of their customers

(OutFocus.2). Another key item is the workers' perception that their organizations have a customer focus (r=0.41, OutFocus.1). Two other items, which have been linked to other clusters, also contribute significantly to this cluster through positive correlations with OutFocus.2. The correlation with Efficiency.1 (r=0.33) suggests that meeting customer expectations requires a clear definition of standards and norms for performance evaluation, consistent with appraisal systems such as 360-degree feedback, which includes the rating of employees' performance by various people, including customers (Fletcher, 2001). To meet customer expectations, decisions and changes made at various organizational levels must be communicated to employees (r=0.29, Commun.1), although access to clear communication of the company's business strategy (ClarGoal.1) was negatively correlated with OutFocus.2 (r=-0.26). This may be due to workers' limited participation in higher-level decision-making processes, which restricts their access to information primarily shared among those directly involved in business strategies, including communication that might impact customer experience. A second inverse correlation was observed between OutFocus.2 and SSupport.1 (r=-0.30), indicating that higher levels of commitment to customers may require more time and effort from leaders, reducing their availability to assist employees when they require it. Overall, the fourth cluster combines various macro-level elements, generating interactions between singular characteristics of strategic planning and customer orientation.

Cluster 5

The fifth and final cluster emphasizes the importance of encouraging innovation and risk-taking in order to drive organizational performance. The strongest relationship in this cluster is between the item Effort.2, which represents the employees' willingness to take risks and be innovative, and Innovat.2, which indicates that the company is able to implement good ideas and suggestions from its employees. In order to foster this innovation, employees need to be trained (Training.1) and have clear criteria for evaluating their individual performance (PerfFeed.1). However, communication plays an important role in this cluster, as negative correlations were observed between Effort.2 and both Commun.2 and Commun.1, indicating that the amount and quality of information employees receive about decisions and changes in the company may impact their willingness to take risks and be innovative. Overall, this cluster is focused on organizational innovation and the importance of communication in facilitating it. The study by Kivimäki et al (2000) highlights the interdependence of communication and innovation, particularly when it comes to encouraging employee initiatives and evaluating performance. Encouraging innovation and risk-taking can be a key factor in driving organizational performance, but it requires clear communication, training, and performance evaluation criteria to be successful.

In order to assess the replicability of the study, two first-order confirmatory factor analysis models were employed to determine if the parameter estimates obtained for the Training dataset differ significantly from those derived from the Testing dataset. The results, as displayed in Table 1, reveal that the standardized coefficients and goodness-of-fit indices are similar across both datasets, indicating that the study's findings can be replicated and that similar interaction patterns are likely to emerge in future samples.

Insert Table 1 about here

The identification of the five clusters described earlier provided a solid foundation for the development of the Relational Framework for Organizational Climate (RFOC). This framework was created by considering the most significant associations among the items from the four values models. As depicted in Figure 3, there are a greater number of connections between items from the Human Relations Model and the Rational Goal Model. In addition, two items from the Open Systems Model had high centrality scores. However, the Internal Process Model had a limited number of dimensions and, therefore, only two items established independent connections with items from other models, contributing minimally to the overall framework.

Considering the RFOC as a whole, the most crucial factor in understanding organizational climate is the extent to which employees can participate in decision-making processes that affect their lives. This implies that workers' perceptions are primarily influenced by internal organizational aspects such as their sense of belonging, trust, and cohesion, which also have a positive impact on their well-being. Notably, the focus on internal elements is in contrast with certain aspects of the Open Systems Model and the Rational Goal Model, which are more externally oriented. For example, an increased level of participation and communication is negatively associated with the acceptance of organizational change and the acceptance of risks. This relationship has been explored in previous literature with regard to poorly managed communication (Bordia et al., 2003; Smet et al., 2016; Kraft & Spiro, 2019). However, taking calculated risks to improve company performance is perceived as one of the top items in the network. Therefore, each element of organizational climate, despite its interconnectedness with elements from other models, must be examined independently.

Insert Figure 3 about here

Conclusions

The Competing Values Model has been widely adopted as a framework for investigating organizational effectiveness and provides a comprehensive conceptual map for understanding organizational climate. This study has applied psychological networks to demonstrate how researching organizational climate can assist HR and Organizational Psychology professionals, as well as academic staff, in developing unique knowledge and understanding of worker and workplace relations to improve organizational climate.

Furthermore, it can aid in advancing the measurement of organizational climate from a common factor approach, where the dimensions are interpreted as part of a single values domain, to a more dynamic and extensive relational framework, with the elements of a values domain collaborating to explain the entire system more holistically. This perspective is in line with the discussion of Patterson et al.'s study, which emphasizes the interactive nature of the different values domains and the complexity involved in its measurement.

This study contributes to advanced knowledge by explaining how the dimensions of organizational climate from four major schools of organizational effectiveness relate to one another. It introduces the use of psychological networks to the field of organizational psychology and provides a consistent multidimensional framework for investigating not only organizational climate but also a variety of other organizational behaviors.

The study's findings provide valuable insights that can inform the development of survey instruments and organizational policies. Firstly, the study highlights the importance of tailoring survey items to the specific organizational climate of each organization. Secondly, the study suggests that organizations can improve their climate by focusing on the most relevant aspects of organizational climate, depending on their dominant values model. For example, organizations that prioritize the Human Relations Model could improve communication channels and foster more inclusive policy planning processes to increase employee participation and enhance perceptions of the organizational climate. Conversely, organizations that prioritize the Rational Goal Model should ensure that employees are familiar with performance appraisal criteria and provide support to encourage calculated risk-taking to improve results. Attention should also be given to items that have a significant impact on the overall organizational climate, such as "work processes are well planned" (Reflex.1), which interacts with other items from different models.

The study also highlights the usefulness of psychological networks in explaining organizational climate and suggests that HR professionals can utilize centrality measures and community detection algorithms to gain further insights into relationships among variables at both the organizational and group levels. This information can help organizations go beyond individual item frequencies and develop weighted scoring models that prioritize variables with higher levels of centrality. Overall, the study provides a multidimensional framework for investigating organizational climate and demonstrates the potential benefits of applying psychological networks in organizational research.

Given the intricate nature of this investigation, several limitations must be taken into account. First, as the item bank was formulated from responses of workers from various organizations, not all items were administered to all organizations, which resulted in nonrandom missingness. This issue is commonly encountered in computerized adaptive tests, and methods such as multiple imputation are sometimes used to mitigate data sparseness. However, we chose to analyze the data using the sparse matrix, as psychometric techniques can handle missing values. This approach resulted in the exclusion of around 36% (n=151) of the total number of items initially available for item pooling.

Second, although most companies participated in the study several times over the years, we could not track individual responses across applications due to the anonymized nature of the data. This structural limitation prevented us from conducting a longitudinal study and accounting for the non-independence of the data resulting from repeated observations, such as the same employee participating in different years.

Finally, this study extends Patterson et al.'s framework to a non-European culture. It would be beneficial to have comparative studies or studies from other cultures that follow a similar approach and contribute to the literature on organizational climate using a network analysis method. This would enhance the organizational psychology literature and our comprehension of organizational climate in diverse settings. Future research could employ the same framework developed here to expand knowledge on how the different domains of the Competing Values Model are interconnected and how the most central elements interact in distinct cultures.

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Figure 1
Graphical representation of the organizational climate network for the training and testing datasets (n = 526,559 cases each)

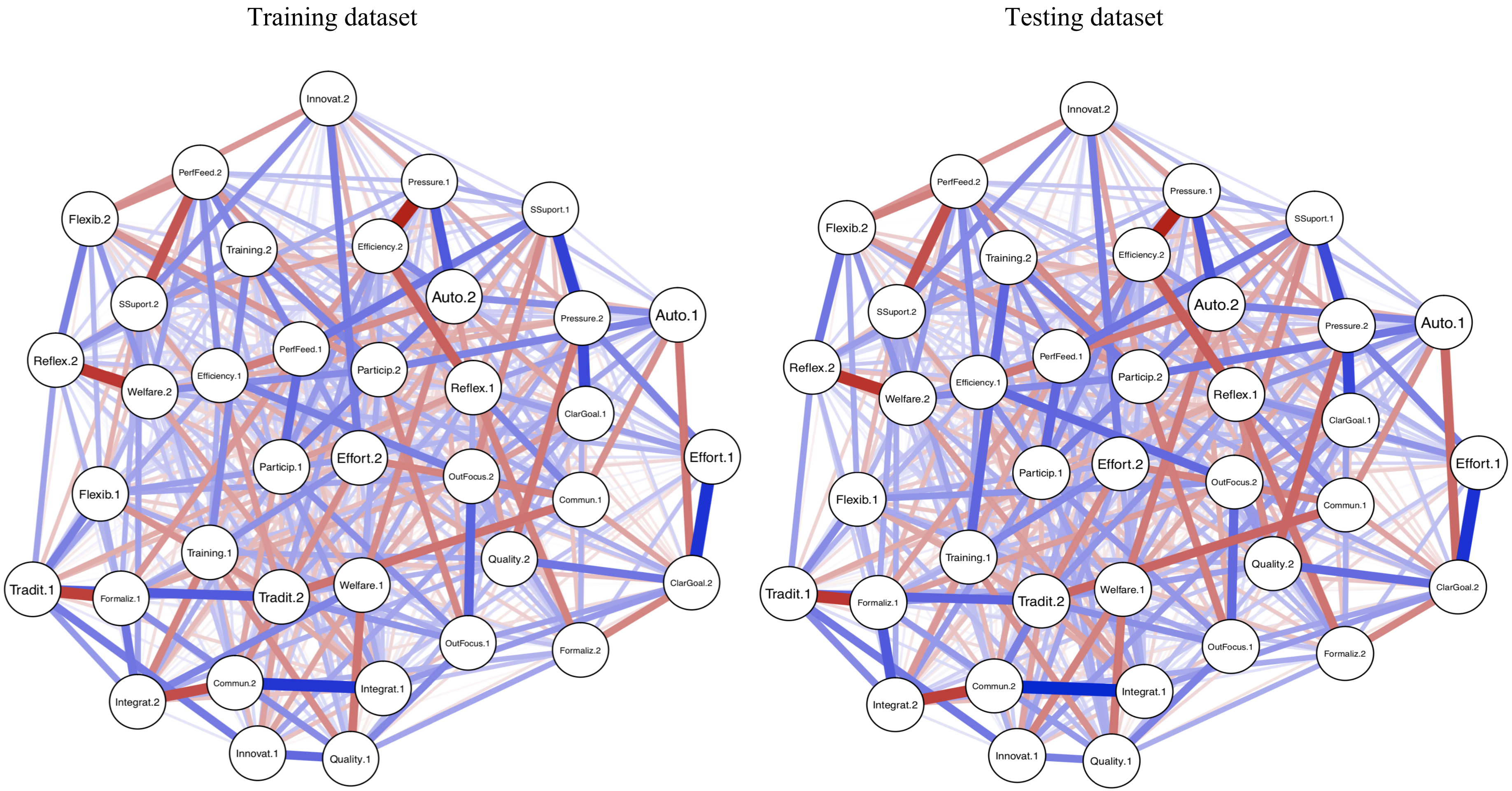


Figure 2
Strength of the items measuring organizational climate for the Training and Testing datasets (n = 526,559 cases each)

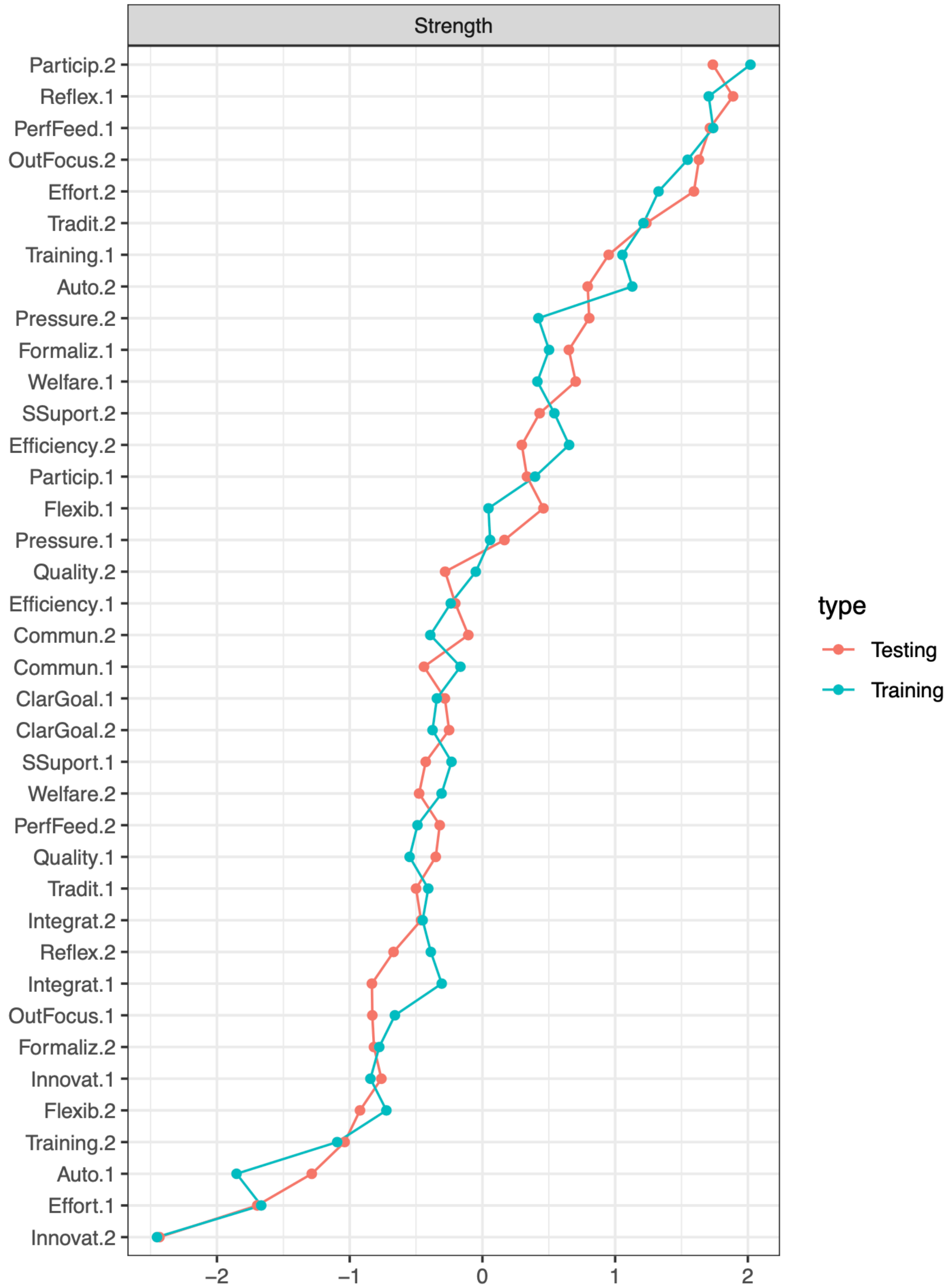


Table 1.
Confirmatory Factor Analysis between Training and Testing datasets.

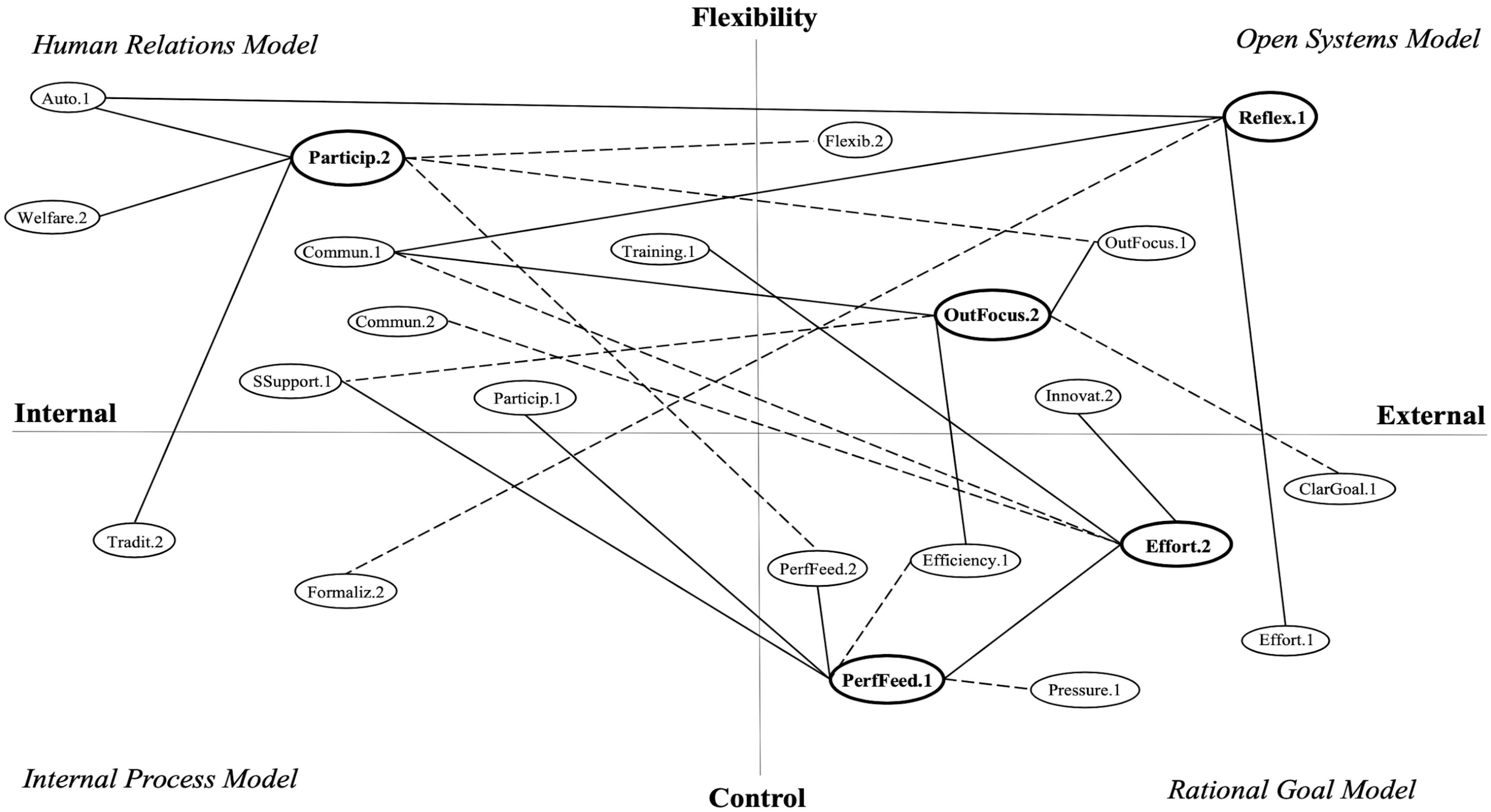
	Training		Testing	
Items	**Standardized Estimates**	**R-squared**	**Standardized Estimates**	**R-squared**
Quality.1	0.70	0.50	0.70	0.50
Innovat.2	0.88	0.58	0.88	0.58
Welfare.1	0.87	0.57	0.88	0.58
Effort.2	0.79	0.52	0.82	0.54
Tradit.1	0.84	0.53	0.84	0.54
Pressure.2	0.64	0.33	0.65	0.33
ClarGoal.1	0.66	0.35	0.67	0.35
Formaliz.2	0.80	0.50	0.80	0.50
Reflex.1	0.87	0.56	0.85	0.55
Commun.1	0.83	0.46	0.83	0.47
Pressure.1	0.68	0.37	0.68	0.37
Commun.2	0.79	0.51	0.78	0.50
Effort.1	0.90	0.59	0.91	0.60
Tradit.2	0.56	0.42	0.57	0.41
Particip.2	0.78	0.42	0.81	0.44
Auto.1	0.71	0.44	0.71	0.44
SSuport.1	0.73	0.39	0.73	0.38
SSuport.2	0.74	0.49	0.74	0.49
Formaliz.1	0.88	0.59	0.88	0.58
Training.2	0.77	0.44	0.77	0.44

Particip.1	0.91	0.50	0.92	0.51
Auto.2	0.95	0.59	0.95	0.59
Integrat.1	0.75	0.48	0.75	0.48
Integrat.2	0.74	0.43	0.74	0.43
Flexib.1	0.57	0.33	0.56	0.31
Training.1	0.86	0.52	0.86	0.53
Flexib.2	0.65	0.42	0.66	0.43
OutFocus.2	0.56	0.41	0.55	0.39
ClarGoal.2	0.78	0.55	0.77	0.54
Reflex.2	0.74	0.45	0.75	0.45
Efficiency.2	0.54	0.34	0.54	0.34
Quality.2	0.54	0.32	0.55	0.33
PerfFeed.2	0.89	0.48	0.89	0.48
Efficiency.1	0.87	0.52	0.88	0.52
PerfFeed.1	0.87	0.45	0.87	0.45
Innovat.1	0.81	0.58	0.80	0.58
Welfare.2	0.99	0.59	1.00	0.60
OutFocus.1	0.60	0.39	0.60	0.39

Note: All parameters' estimates were significant at 0.001. Training dataset: χ^2 (665) = 109295.58, $p < .001$; AIC = 11714019.70; BIC = 11715293.44; RMSEA = .02; SRMR = 0.06. Testing dataset: χ^2 (665) = 110179.21, $p < .001$; AIC = 11705789.14; BIC = 11707062.88; RMSEA = .02; SRMR = 0.06.

Figure 3

Relational Framework of Organizational Climate based upon Patterson's et al (2005) dimensions related to Quinn and Rohrbaugh's Competing Values Model.



Note: Solid lines represent positive associations, while dashed lines represent negative associations. The dimension with the highest centrality within a cluster is indicated in bold.