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Who Manages B2B Relationships? A Hybrid Cluster Analysis of Demographic, Occupational, And Organizational Profiles in Indonesia

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Abstract: This study aims to identify the profiles of individuals engaged in business-to-business (B2B) relationships in Indonesia and to evaluate the consistency and external relevance of these profiles. The study employs an exploratory quantitative approach using a cross-sectional survey design. A total of 273 responses that met the criteria were analyzed using sequential hybrid clustering, which combines Two-Step Cluster Analysis and K-Modes. Cluster formation was based on age, education, work experience, job title, and field of work, while company size, industry, and type of business partner were used as external validation variables. The results identified five profiles of B2B relationship practitioners: operational relationship professionals, early-career commercial staff, highly educated commercial staff, commercial supervisors, and support function staff. Differences in profiles are primarily shaped by job function, education, age, and job level. Cluster distributions also vary based on company size, industry, and the type of primary business partner. A comparison of TwoStep and K-Modes showed a moderate level of convergence, indicating that the cluster solutions are adequate for exploratory interpretation but still require further validation. These findings expand B2B segmentation from customers and buyer companies to the individuals who manage interorganizational relationships. In practical terms, the resulting profiles can help companies tailor training, staffing, career development, and cross-functional coordination.

Keywords: B2B marketing, relationship actors, segmentation, K-Modes, hybrid clustering

INTRODUCTION

Business-to-business (B2B) marketing takes place through interorganizational relationships managed by individuals from various functions and levels of authority. These individuals communicate, negotiate, exchange information, coordinate work, and resolve issues with business partners. In the B2B literature, they are often understood as "boundary spanners"—actors who bridge the needs of customers and external partners with a company's internal resources and processes. This role is not limited to sales personnel but is also carried out by staff in marketing, operations, procurement, distribution, services, and technical

functions. Prior (2016), Dekker et al. (2019), Piercy (2009), and Geiger and Finch (2009) demonstrate that the effectiveness of B2B relationships heavily depends on the ability of boundary-spanning actors to manage customer needs, internal coordination, and inter-organizational relationships.

The heterogeneity of these actors is also reflected in the concepts of the buying center and the selling center. An organization's purchasing decisions involve individuals with varying levels of knowledge, influence, and authority. At the same time, the selling company requires coordination across multiple functions to design an offer and fulfill commitments to the customer. Cabanelas et al. (2023) emphasize that the purchasing situation and the organizational context influence the configuration of the buying center. On the supplier side, coordination between marketing and sales remains a challenge because the two functions may have different orientations, priorities, and performance metrics. Furthermore, marketing activities in B2B companies are often spread across various units, making customer value creation a cross-functional responsibility rather than the sole responsibility of the formal marketing department (Biemans et al., 2022; Blachetta & Kleinaltenkamp, 2019; Guo & Wang, 2015).

Although the literature acknowledges the diversity of B2B stakeholders, segmentation research still tends to focus primarily on customers, accounts, buyer companies, or markets. Segmentation is used to identify groups with similar needs and characteristics so that marketing strategies and resources can be tailored more effectively. Freytag and Clarke (2001) provide a foundation for business market segmentation, while Mora Cortez et al. (2021) demonstrate that B2B segmentation must be understood as a process encompassing the identification, implementation, and evaluation of groups. Subsequent research also emphasizes the importance of the theoretical foundation, strategic relevance, multidimensionality, and stability of segmentation in a dynamic business environment (Blocker & Flint, 2007; Ritter & Pedersen, 2024; Tang & Mantrala, 2024). B2B relationships also need to be understood as part of a network of interdependent actors, not merely as an exchange between a single buyer and a single seller (Gummesson & Polese, 2009).

These segmentation principles can be extended from customers to the individuals involved in B2B relationships. B2B actors may differ based on age, education, work experience, job title, and field of work. Combinations of these characteristics can form profiles such as commercial staff in the early stages of their careers, operational staff responsible for service delivery, or supervisors who coordinate various functions. Treating all individuals as a homogeneous group risks obscuring important differences in capabilities, responsibilities, training needs, and decision-making authority.

A gap in the existing research lies in the limited number of studies that group B2B relationship actors based on a configuration of individual and job characteristics. The boundary-spanning literature generally addresses the behavior or roles of actors, whereas the segmentation literature primarily groups customers and companies. This study bridges these two perspectives by treating individuals involved in inter-organizational relationships as the objects of segmentation. This focus also aligns with the need to produce B2B research that is closely grounded in empirical phenomena and provides value to decision-makers (Ojansivu, 2024).

The study employs sequential hybrid clustering by combining Two-Step Cluster Analysis and K-Modes. Age, education, work experience, job title, and field of work are used as cluster-forming variables. Company size, industry, and type of primary partner are used to evaluate the external validity of the profiles. This approach allows the number and characteristics of clusters to be determined based on empirical patterns rather than being predetermined.

Given this gap, this study aims to identify the profiles of B2B relationship actors in Indonesia, describe the characteristics that distinguish each profile, and assess the consistency of the cluster structures generated by TwoStep Cluster Analysis and K-Modes. This study

contributes by expanding the scope of B2B segmentation from customers to individuals, integrating the perspectives of boundary spanning and cross-functional activities, and offering a segmentation approach validated using two clustering methods.

Cluster analysis is essentially an exploratory approach aimed at identifying homogeneous groups based on the similarity of their members' characteristics. Nevertheless, hypothesis development remains necessary to provide a theoretical basis for selecting cluster-forming characteristics, interpreting the resulting profiles, and testing the external validity of the segmentation solutions. The hypotheses in this study are not intended to test causal relationships, but rather to test the existence of heterogeneity, differences in profile distributions, and the consistency of clustering results.

This approach aligns with the configurational nature of B2B segmentation. Individual and occupational characteristics are not treated as standalone predictors but rather as combinations of attributes that collectively form specific profiles. Thus, this study focuses on identifying configurations of B2B relationship actors based on demographic, occupational, and organizational characteristics.

Business-to-business relationships do not merely occur between two organizations as formal entities. These relationships are carried out through the interactions of individuals who represent their companies in communicating, negotiating, exchanging information, coordinating activities, and resolving issues with business partners. These individuals may come from marketing, sales, key account management, operations, distribution, logistics, customer service, procurement, or technical functions.

In B2B marketing literature, individuals who bridge the gap between an organization and external parties are known as boundary-spanning actors. They play a role in translating customer needs into internal company processes, conveying market information, coordinating resources, and maintaining the continuity of inter-organizational relationships. Prior (2016) demonstrates that boundary spanners play a crucial role in the implementation of business solutions because they must adapt service approaches to customer needs and situations. Dekker et al. (2019) also found that the relational behavior of boundary spanners is linked to coordination and control mechanisms within supply chain relationships.

The buying center perspective further reinforces the view that B2B relationship actors are not a homogeneous group. Organizational purchasing decisions generally involve several individuals with different roles, knowledge, levels of influence, and authority. Cabanelas et al. (2023) explain that the purchasing situation, decision complexity, and organizational context influence the composition of the buying center. On the seller's side, a similar configuration emerges through the involvement of actors from sales, marketing, technical, operational, and managerial functions.

This heterogeneity is also evident in the distribution of marketing activities within B2B organizations. Blachetta and Kleinaltenkamp (2019) demonstrate that marketing activities are not always centralized within a formal marketing department. Activities related to customers and the market can be dispersed across sales, service, operations, and technical units. Their analysis reveals several configurations of marketing activity distribution, indicating that there is no single organizational structure applicable to all B2B companies.

Biemans et al. (2022) also emphasize that the interface between marketing and sales is dynamic and influenced by the division of responsibilities, organizational structure, technology, and market characteristics. The marketing and sales functions may differ in their time orientation, performance metrics, and level of proximity to customers. Additionally, operational and logistics functions play a role in delivering the value promised to business customers.

The literature on B2B segmentation assumes that business markets consist of heterogeneous actors. Ritter and Pedersen (2024) explain that segmentation provides a systematic framework for identifying differences relevant to B2B marketing decision-making.

Tang and Mantrala (2024) demonstrate that multidimensional segmentation can yield more meaningful groups compared to approaches that use only a single segmentation criterion.

Although most B2B segmentation research focuses on customers or buyer organizations, the principle of heterogeneity can also be applied to the individuals managing B2B relationships. B2B relationship managers may differ based on age, education, work experience, job level, and field of work. Combinations of these characteristics can represent career stages, human capital, levels of authority, and functional positions within an organization.

For example, one profile might consist of commercial staff in the early stages of their careers. In contrast, another profile might be dominated by experienced operational staff or professionals at the supervisory level. However, these categories are not predetermined prior to analysis. Profiles and cluster labels are determined based on empirical patterns that emerge from the data.

Based on this reasoning, the first hypothesis is formulated as follows:

H1: B2B relationship actors can be grouped into different profiles based on the configuration of age, education, work experience, organizational position, and field of work.

Company size is related to the complexity of organizational structure, the level of formalization, division of labor, and functional specialization. Large companies generally have more adequate resources to establish separate units for marketing, sales, key account management, operations, distribution, logistics, and customer service. Within such a structure, individual responsibilities tend to be more specific and clearly defined. Conversely, micro and small companies generally have simpler structures and a more limited number of employees. A single employee may perform multiple functions simultaneously, such as acquiring customers, processing orders, coordinating shipments, and resolving complaints. These conditions can result in a more multifunctional profile of B2B relationship actors.

Findings by Blachetta and Kleinaltenkamp (2019) indicate that the distribution of marketing activities within B2B companies varies depending on organizational arrangements. Some companies centralize marketing activities within a formal unit, while others distribute these activities across various functions. These differences suggest that the configuration of B2B relationship actors may be related to a company's scale and structure. Company scale was not used as a cluster-forming characteristic in this study. Instead, this variable served as the basis for external validation to examine whether the resulting profiles exhibited different distributions across micro, small, medium, and large companies. This distinction was necessary to ensure that company scale categories did not directly determine the cluster solutions.

Based on this reasoning, the second hypothesis is formulated as follows:

H2: The distribution of B2B relationship actor profiles differs significantly based on company size categories.

B2B marketing activities take place within an industrial context characterized by varying levels of product complexity, service intensity, channel structure, transaction frequency, and coordination needs. Differences in industrial context can influence the functions involved in relationships with business partners and the characteristics of the individuals managing those relationships.

In manufacturing companies, B2B relationships may involve sales personnel, technical staff, production staff, quality control, operations, and logistics. Interactions with customers may include product specifications, production schedules, inventory management, quality standards, and on-time delivery. In distribution and retail companies, B2B relationships may involve sales, marketing, merchandising, account management, and distribution functions to a greater extent. Companies in the fast-moving consumer goods sector also require intensive coordination between marketing, sales, distribution, and logistics due to the high frequency of transactions and the extensive channel network.

Parvinen et al. (2013) show that product-oriented and service-oriented companies differ in how they systematize sales activities. These findings indicate that how a company organizes

customer interactions and the process of delivering value is influenced by its business characteristics. The industry context is not used as a cluster-forming variable. Instead, it is treated as an external variable to assess whether the profiles of B2B relationship actors are concentrated in specific industry contexts. Thus, the study can test the relevance of the profiles without allowing industry categories to determine the cluster structure from the outset.

Based on this reasoning, the third hypothesis is formulated as follows:

H3: The distribution of B2B relationship actor profiles differs significantly by industry category.

The structure of B2B relationships may vary depending on the type of primary partner a company deals with. Relationships with suppliers, distributors, retailers, business customers, and agents require different patterns of information exchange, operational coordination, negotiation, and dependency management.

Relationships with suppliers may emphasize procurement activities, input quality, supply continuity, and on-time delivery. Relationships with distributors may require sales coordination, inventory management, channel support, and market development. Meanwhile, relationships with retailers or business customers may involve more account management, commercial negotiations, service fulfillment, product availability, and complaint handling.

Cabanelas et al. (2023) explain that the decision-making context and the characteristics of business relationships influence the composition and participation of actors in an organization's purchasing process. These findings suggest that companies interacting with different types of partners may require distinct configurations of commercial, operational, and managerial personnel. The type of business partner is not positioned as a factor causing the formation of a specific profile. However, differences in cluster distribution based on partner type may indicate that the resulting profiles have substantive relevance in the context of B2B channels. The type of primary business partner is not included as a cluster-forming variable and is used as an external validation variable.

Based on this reasoning, the fourth hypothesis is formulated as follows:

H4: The distribution of B2B relationship actor profiles differs significantly based on the type of primary business partner.

The quality of segmentation is determined not only by an algorithm's ability to generate a certain number of clusters but also by the stability and interpretability of those clusters. A clustering solution that relies entirely on a single algorithm may reflect the technical characteristics of the method used rather than the structure actually presents in the data.

Each clustering algorithm has different procedures for calculating dissimilarity, determining cluster centers, selecting the number of clusters, and allocating cases. Therefore, the solutions obtained from one method need to be compared with those from other methods to assess their consistency. This study employs a sequential hybrid clustering approach that combines Two-Step Cluster Analysis and K-Modes. Two-Step Cluster Analysis is used in the exploratory phase to identify the most appropriate number of clusters. This method uses the log-likelihood distance measure and can evaluate solutions based on the Bayesian Information Criterion and the silhouette coefficient.

Once the number of clusters was determined, K-Modes was used to regroup the respondents into the same number of clusters. K-Modes was chosen because all the characteristics used to form the clusters were categorical. Unlike K-Means, which uses mean values as cluster centers, K-Modes uses dominant categories or modes as representations of cluster centers. Nie et al. (2021) emphasize that classification results must be validated to ensure that the resulting clusters not only exhibit statistical fit but are also stable and managerially relevant. The use of a second method allows researchers to assess whether the cluster solutions reflect systematic patterns or are merely artifacts of a specific algorithm.

If the profile structure in the data is sufficiently strong, respondents placed in the same group via Two-Step Cluster Analysis should tend to be placed in corresponding groups via K-

Modes. This consistency can be assessed using membership cross-tabulations, percentage agreement, the Adjusted Rand Index, or Cohen's Kappa.Perfect agreement is not a requirement because the two methods use different clustering procedures. However, an adequate level of convergence will enhance the credibility of the segmentation solution.

Based on this reasoning, the fifth hypothesis is formulated as follows:

H5: The cluster memberships generated by Two-Step Cluster Analysis and K-Modes demonstrate an adequate level of convergence.

These five hypotheses form the theoretical and methodological foundation of the study (Figure 1). The first hypothesis tests the existence of distinct profiles among B2B relationship actors. The second through fourth hypotheses evaluate the external validity of the profiles based on company size, industry context, and type of business partner. The fifth hypothesis evaluates the consistency of the segmentation solutions by comparing the two clustering algorithms.

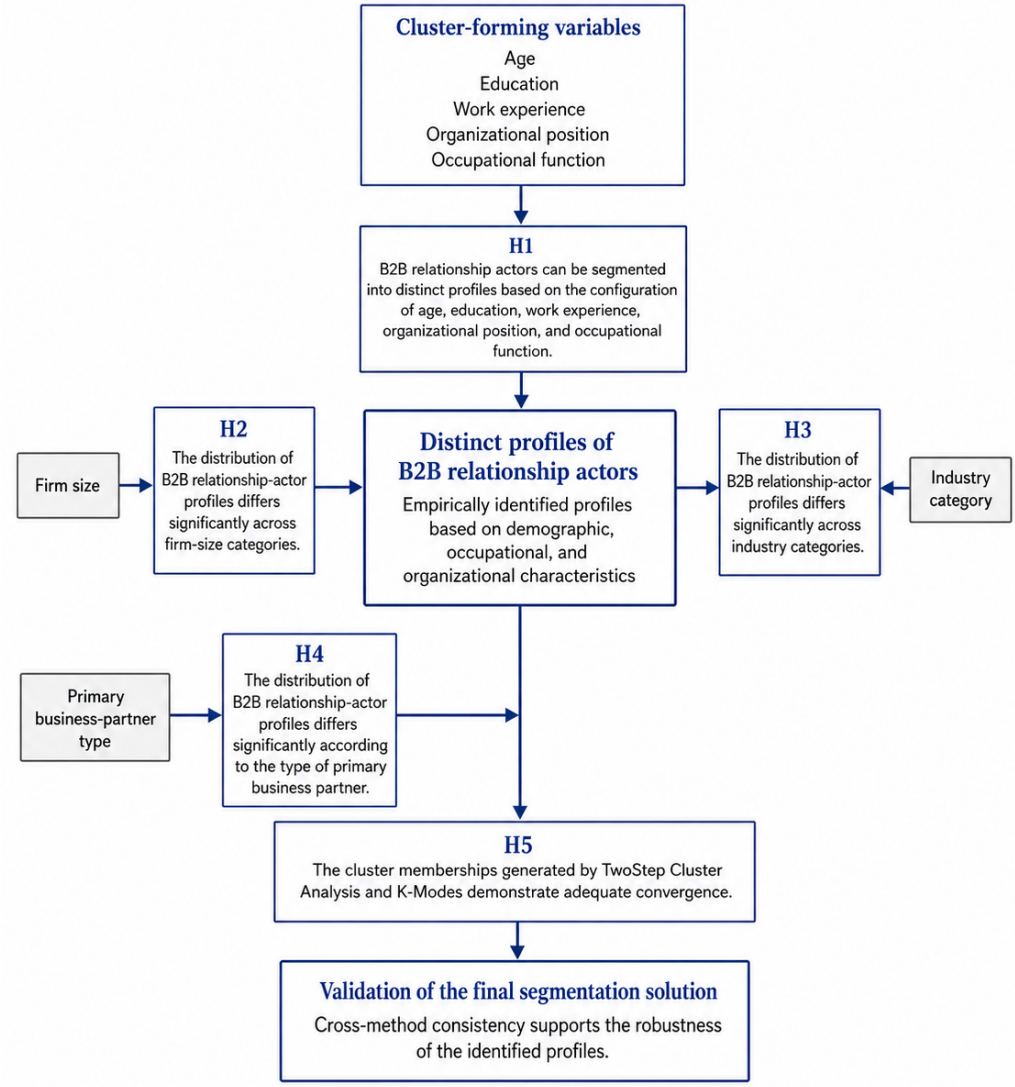

Figure 1. Hypothesis Development

METHOD

Research Design

This study employs an exploratory quantitative approach with a cross-sectional survey design. The purpose of the analysis is not to test causal relationships or structural models, but rather to identify the natural configurations of individuals involved in business-to-business

(B2B) relationships. The unit of analysis is individuals who interact with business partners through marketing, sales, operations, distribution, logistics, or other support functions.
A segmentation approach was chosen because the characteristics of B2B relationship actors are not assumed to be homogeneous. Rather than assessing the influence of a single characteristic in isolation, the research grouped respondents based on combinations of age, education, work experience, job level, and field of work. This approach is consistent with the view that B2B segmentation must capture heterogeneity that is both theoretically meaningful and actionable from a managerial perspective (Ritter & Pedersen, 2024; Tang & Mantrala, 2024).

The analysis was conducted using sequential hybrid clustering. The first stage employed a categorical TwoStep procedure to explore the cluster structure. The second stage utilized K-Modes to assess the stability and interpretability of the solution. Firm characteristics and market context were not used to form clusters but were employed as external validation once the clusters were established.

Population, Unit of Analysis, and Sampling Technique

The target population consists of individuals working at companies engaged in B2B activities in Indonesia who are involved in managing relationships with distributors, suppliers, retailers, business customers, agents, or other inter-company partners. Respondents may come from manufacturing companies, distributors, modern retailers, FMCG firms, and other industrial or service sectors. The results are shown in Table 1.

Respondents were selected using purposive sampling. To align with the unit of analysis, respondents had to meet four criteria: (1) the company engages in B2B activities; (2) the respondent is involved in activities related to business partner relationships; (3) the respondent has worked at the current company for at least two years; and (4) the respondent understands the process of collaboration or relationships with the company's partners.

The questionnaire was distributed online via professional networks, email, LinkedIn, and industry networks. Data collection took place from April 28 to June 30, 2026. Company names were not used in clustering or validation analyses to maintain focus on individual characteristics and reduce the risk of organizational identity disclosure.

Table 1. Screening Process and Determination of the Analysis Sample

Stage	n	Response %
Responses Received	304	100.0
The company does not engage in B2B	7	2.3
Not in a relationship or did not proceed with screening	1	0.3
Length of service at the company <2 years	23	7.6
Responses that met all screening criteria	273	89.8
Complete cases for cluster-forming variables	273	89.8

Data and Variable Preparation

All cluster-forming variables are categorical. Categories were merged to a limited extent to avoid categories with very low frequencies and to improve the interpretability of the profiles. Bachelor's, master's, and doctoral degrees were combined into the category "bachelor's or higher." The positions of manager and senior manager/director were combined into "manager or higher." The fields of marketing and sales were combined into the "commercial function, while operations and distribution/logistics were combined into the "operations" function (Table 2).

Table 2. Operationalization of variables in the clustering analysis

Variable	Role	Analysis Category	Representation
Age	Cluster formers	<25; 25–30; 31–40; >40 years	Career Stage
Education	Cluster formers	High school or equivalent; Associate degree; bachelor's degree or higher	Formal human capital
Total work experience	Cluster formers	<2; 2–5; 6–10; >10 years	Cumulative experience
Position	Cluster formers	Staff; Supervisor; Manager or higher	Level of authority
Field of work	Cluster Formers	Commercial; Operational; Other	Functional position
Company size	External validation	Micro/Small; Medium; Large	Organizational structure
Industry	External validation	Manufacturing; Distributors; Modern retail; FMCG; Others	Business context
Main Partner Types	External validation	Distributors; Suppliers; Retailers/business customers; Agents/brokers	Channel context
Gender and region	Additional profiles	Original categories on the questionnaire	Cluster description

Partner type responses that could not be mapped to the four conceptual categories, for example, responses consisting of job titles or industries, were classified as unidentified. These responses were retained in cluster formation because partner type is not a clustering variable but were excluded listwise from partner-type-specific validation. Therefore, the partner-type test used 212 classifiable responses.

RESULTS AND DISCUSSION

Data Profile

The valid sample is relatively balanced by gender but concentrated in the younger age group, the 2–5 years of experience group, and the staff-level position group. Commercial functions account for 48.4% of respondents, operational functions for 38.5%, and other functions for 13.2%. The dominance of the 2–5 years of experience category and staff-level positions should be considered in the interpretation, as these two variables have lower discriminatory power compared to job field, age, and education (Table 3 and Figure 2).

Table 3. Characteristics of the valid sample

Characteristics	Category	n	%
Gender	Male	142	52.0
	Female	131	48.0
Age	25–30 years	149	54.6
	<25 years	77	28.2
	31–40 years	39	14.3
	>40 years	8	2.9
Education	Bachelor's degree or higher	148	54.2
	High school or equivalent	91	33.3
	Diploma	34	12.5
Work experience	2–5 years	241	88.3
	6–10 years	18	6.6
	<2 years	9	3.3

	>10 years	5	1.8
Position	Staff	227	83.2
	Supervisor	38	13.9
	Manager or higher	8	2.9
Field of work	Commercial	132	48.4
	Operations	105	38.5
	Other	36	13.2
Company size	Large	116	42.5
	Medium	91	33.3
	Micro/small	66	24.2
Operational area	Greater Jakarta	183	67.0
	Other regions	44	16.1
	West Java	30	11.0
	East Java	16	5.9

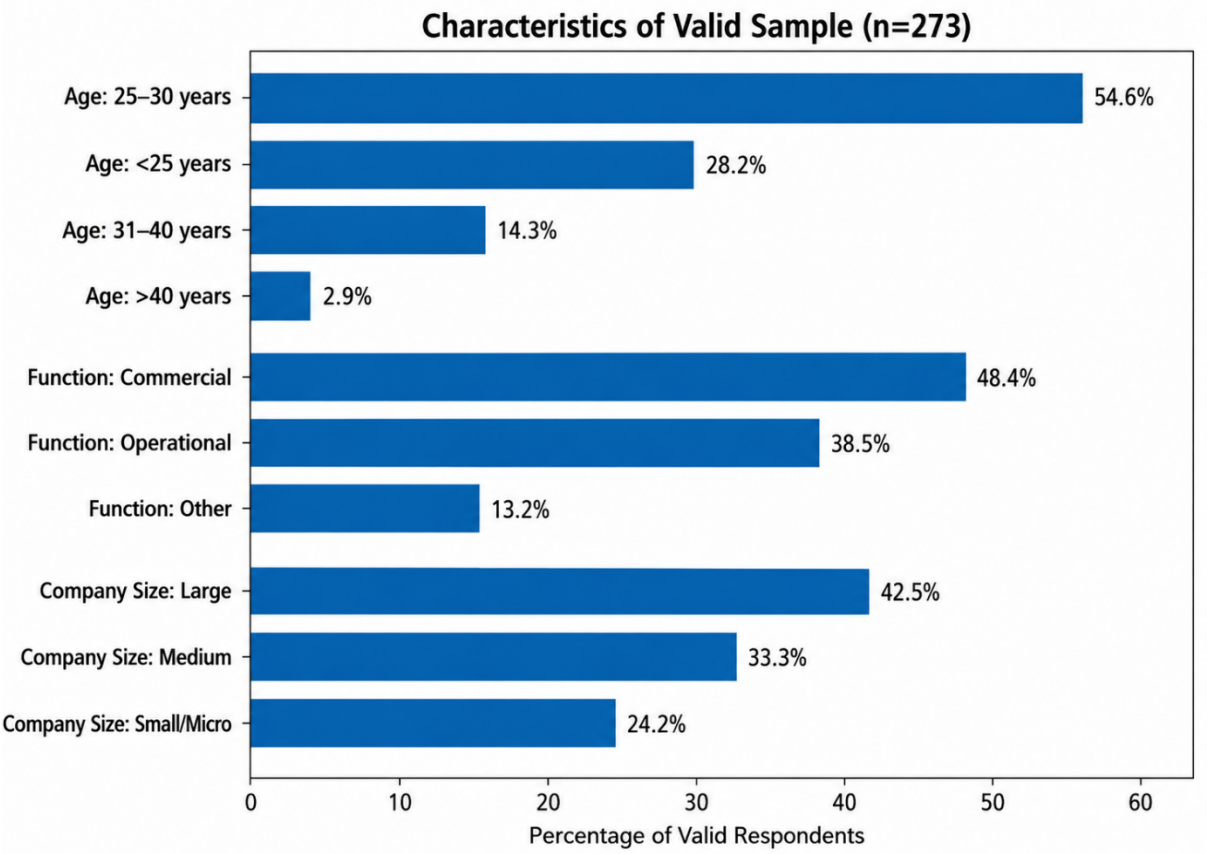

Figure 2. Distribution of selected characteristics of valid respondents

Analysis Strategy

Descriptive analysis and data verification

The first stage involved calculating the frequency and percentage of each category, checking data completeness, and evaluating very rare categories. Since all 273 valid respondents had complete data on the five cluster-forming variables, no imputation was performed. Individual company data were not used as cluster formers. The sequential hybrid clustering and validation stages are shown in Figure 3.

Categorical TwoStep Procedure

The TwoStep procedure was implemented in two stages. First, observations with identical category patterns were combined into preclusters. A total of 64 unique category

patterns were identified among the 273 respondents. Second, the preclusters were merged agglomeratively using the increase in categorical entropy loss as a measure of dissimilarity. The merger resulting in the smallest increase in loss was performed iteratively until a solution of two to six clusters was formed.

Solution quality was assessed using the average silhouette coefficient, minimum cluster size, parsimony, and interpretability. A higher silhouette value indicates that observations are closer to their own cluster than to other clusters. However, the decision regarding the number of clusters was not based solely on the highest statistical value, as overly detailed solutions can fragment profiles that are theoretically similar.

$$s(i) = [b(i) - a(i)] / \max\{a(i), b(i)\}$$

Validation Using K-Modes

K-Modes is used as the second method because the cluster-forming variables are entirely categorical. The center of each cluster is represented by the most frequently occurring category—or mode—rather than a numerical mean. The dissimilarity between a respondent and a cluster mode is calculated based on the number of attributes with differing categories.

$$d(x_i, q_c) = \Sigma_j I(x_{ij} \neq q_{cj})$$

K-Modes was run with 120 random initializations for each candidate number of clusters. The solution with the lowest total intra-cluster dissimilarity was retained. The number of clusters in K-Modes was set equal to the candidates compared in the TwoStep procedure so that both methods could be evaluated directly.

Convergence and Selection of the Final Solution

The TwoStep and K-Modes memberships were aligned using optimal label matching. Convergence is assessed using the percentage of agreement, the Adjusted Rand Index (ARI), and Normalized Mutual Information (NMI). The percentage of agreement indicates the proportion of respondents placed in matching clusters, while ARI and NMI correct for similarities that may arise by chance and are independent of cluster label assignments.

The final solution was selected based on six criteria: (1) the silhouette values of both methods; (2) minimum cluster size; (3) inter-method convergence; (4) parsimony; (5) the presence of substantively distinct profiles; and (6) managerial relevance for B2B marketing. This approach follows the principle that segmentation must be validated and that merely producing a technical classification is insufficient (Nie et al., 2021).

External Validation

Once the final profiles were established, cluster distributions were compared based on company size, industry, type of primary partner, gender, and operational region. The chi-square test was used to assess the association between cluster membership and external variables. The strength of the association was reported using Cramer's V.

$$V = \sqrt{[\chi^2 / \{N \times \min(r - 1, c - 1)\}]}$$

All analyses were performed using Python 3.13 with pandas, NumPy, SciPy, scikit-learn, and Matplotlib. The TwoStep and K-Modes procedures were written explicitly to ensure the process could be replicated. The significance level for external validation was set at 5%.

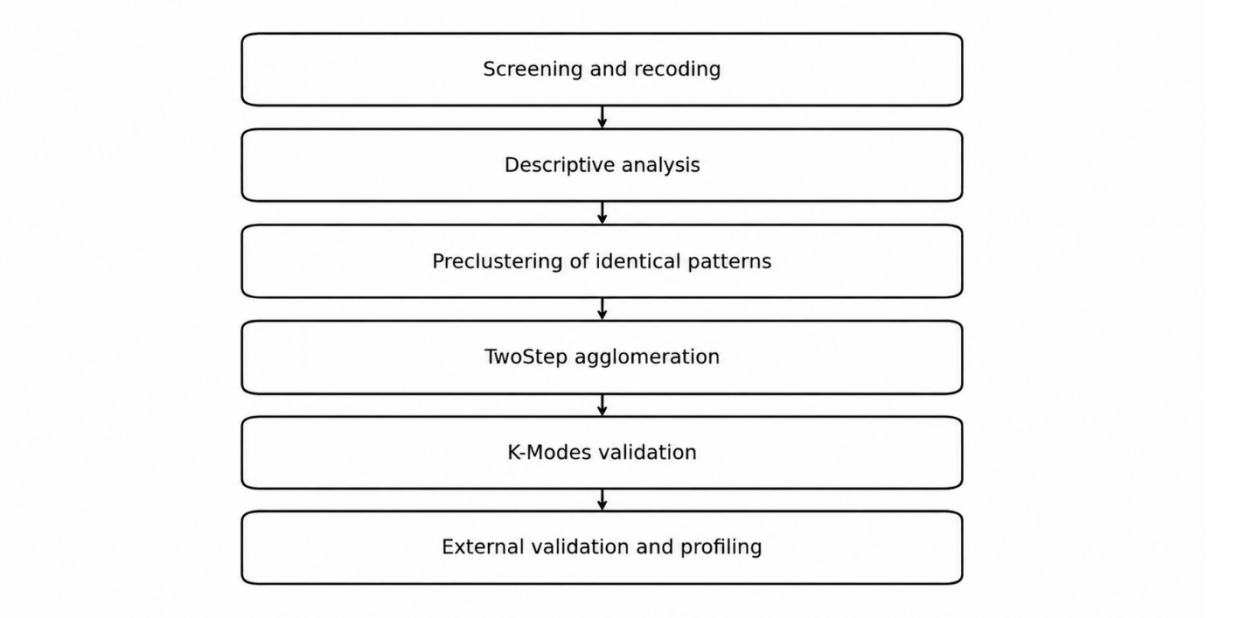

Figure 3. Sequential hybrid clustering workflow and validation

Selection of the Number of Clusters

Solutions with two through six clusters were compared to determine the most appropriate number of clusters. As shown in Table 4, the six-cluster solution yielded the highest silhouette score. However, this solution has several limitations: the smallest cluster in the TwoStep procedure contained only 17 respondents, and the inter-method agreement rate dropped to 60.4%. Furthermore, as shown in Figure 4, the six-cluster solution tends to split the operational group into several subprofiles that exhibit only limited substantive differences.

The five-cluster solution was selected because it provides a better balance between separation quality and interpretability. The TwoStep silhouette of 0.279 and the K-Modes silhouette of 0.274 indicate moderate separation. The smallest K-Modes cluster size was 20 respondents. Inter-method agreement reached 66.3%, with an ARI of 0.370 and an NMI of 0.484. This solution also maintains the commercial supervisor profile as a distinct group, making it more relevant for interpreting the structure of B2B relationship actors.

Table 4. Comparison of cluster solution candidates

k	Silhouette TwoStep	Silhouette K-Modes	K-Modes Cost	Fit	ARI	Min. cluster	Decision
2	0.240	0.268	353	67.0%	0.113	104	
3	0.199	0.302	297	53.1%	0.108	52	
4	0.237	0.281	259	64.8%	0.309	21	
5	0.279	0.274	239	66.3%	0.370	20	Selected
6	0.313	0.306	216	60.4%	0.426	17	

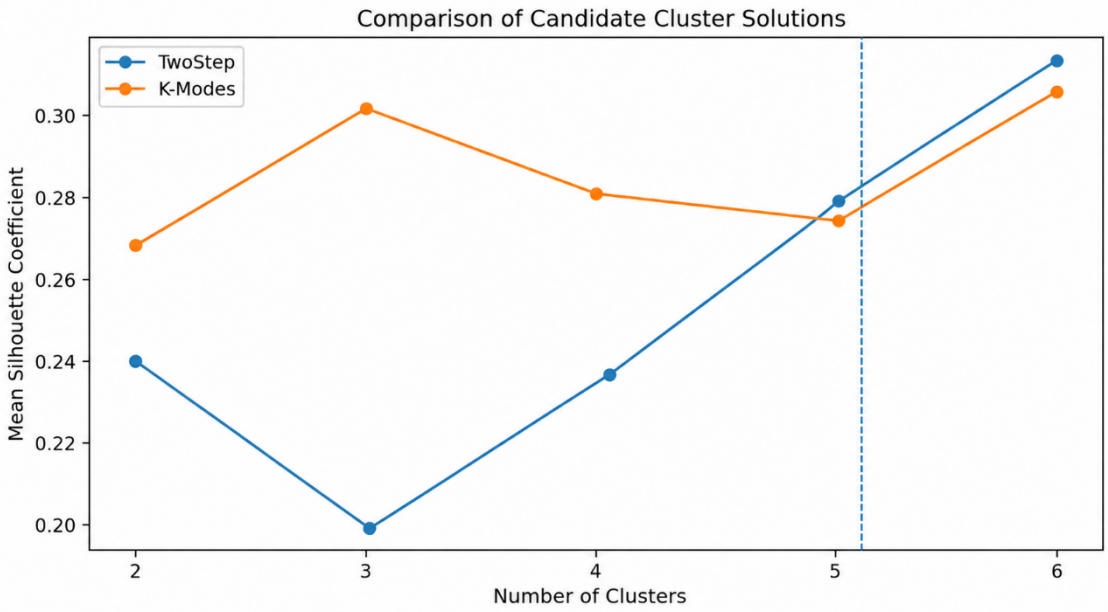

Figure 4. Comparison of silhouette coefficients for two- to six-cluster solutions

Final Cluster Profiles

The K-Modes results for the five-cluster solution were used as the basis for naming the profiles because this method produces modal categories that are easier to interpret. As shown in Table 5, each cluster was labeled based on a combination of dominant characteristics reflecting age, education, position, and job function. Cluster naming in this study is analytical in nature—that is, it is intended to summarize the main patterns in the data—and is not intended as a normative classification of individuals.

The size distribution and proportions of each cluster can be seen more clearly in Figure 5, while the concentration of dominant categories in each profile is visualized in Figure 6. Both figures reinforce that each cluster has distinct characteristic patterns and can be interpreted as relatively distinctive profiles of B2B relationship actors.

Table 5. Characteristic modes and sizes of the five B2B relationship actor profiles

Cluster	Profile	n	%	Age of Capital	Education of Capital	Position	Capital function
C1	Operational Relations Professional	99	36.3	25–30 years	Bachelor's degree or higher	Staff	Operations
C2	Entry-level commercial staff	73	26.7	Under 25 years old	High school or equivalent	Staff	Commercial
C3	Highly educated commercial staff	60	22.0	25–30 years	Bachelor's degree or higher	Staff	Commercial
C4	Commercial Supervisor	21	7.7	25–30 years	Bachelor's degree or higher	Supervisor	Commercial
C5	Support Staff	20	7.3	25–30 years	High school diploma or equivalent	Staff	Other

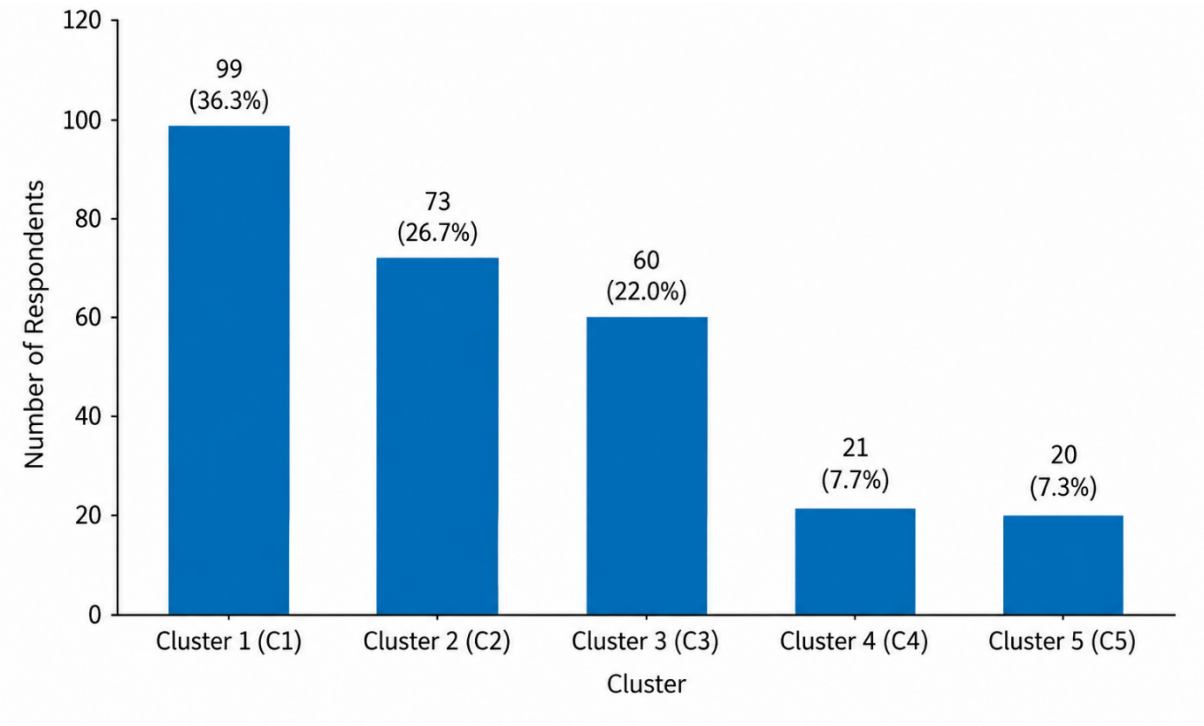

Figure 5. Size and proportion of the five final clusters

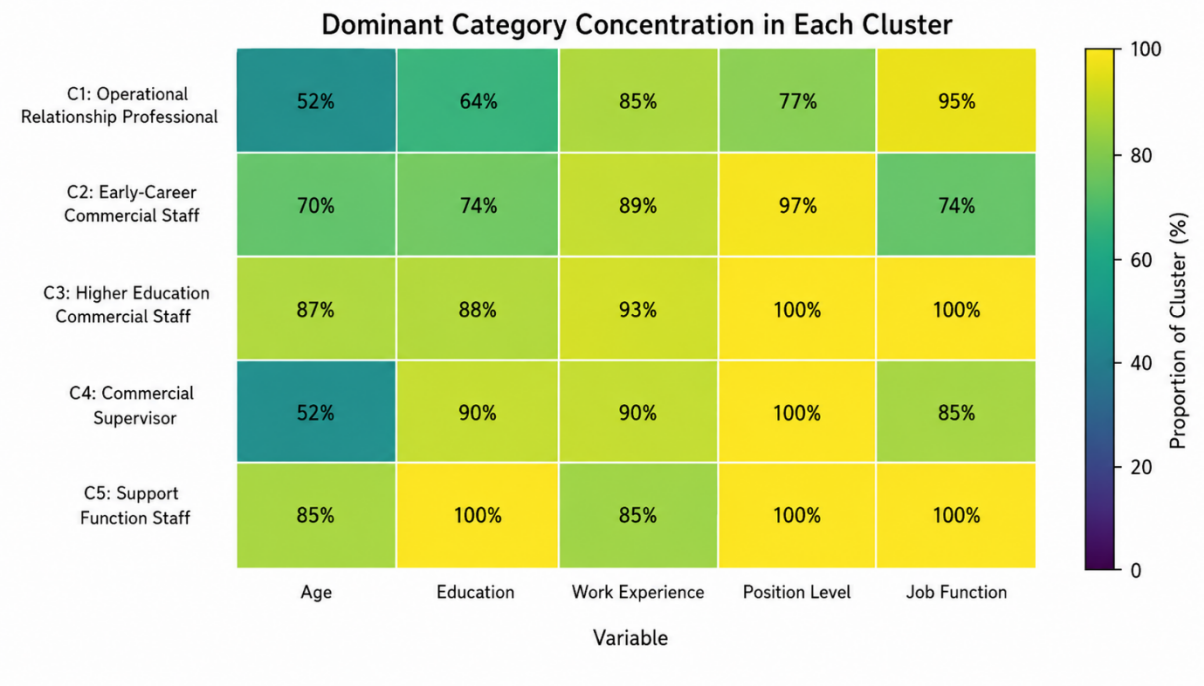

Figure 6. Concentration of dominant categories in each profile

Cluster 1 – Operational Relations Professionals

The largest cluster comprises 99 respondents, or 36.3% of the sample. A total of 94.9% of its members come from operational functions, and 63.6% hold a bachelor's degree or higher. Although 76.8% are staff members, this cluster also includes a larger proportion of supervisors and managers compared to most other clusters. This profile represents individuals who deliver on the B2B value proposition through the coordination of processes, services, distribution, and operational problem-solving.

Cluster 2 – Early-Career Commercial Staff

This cluster consists of 73 respondents, or 26.7%. Most are under 25 years old (69.9%), have a high school diploma or equivalent (74.0%), are at the staff level (97.3%), and work in commercial functions (74.0%). This profile represents a group of sales or marketing practitioners in the early stages of their careers with still-limited formal authority.

Cluster 3 – Highly Educated Commercial Staff

This cluster comprises 60 respondents, or 22.0%. All members work in commercial roles and are at the staff level. A total of 88.3% hold a bachelor's degree or higher, and 86.7% are aged 25–30. Compared to Cluster 2, this profile represents commercial staff who are more concentrated in terms of higher education and early-to-mid-career age.

Cluster 4 – Commercial Supervisors

This cluster consists of 21 respondents, or 7.7%. All members are at the supervisor level; 90.5% hold a bachelor's degree or higher, and 85.7% work in commercial functions. This profile represents the group with the most clearly defined coordinating authority and the potential to serve as a liaison between commercial staff, management, and operational functions.

Cluster 5 – Support Function Staff

The smallest cluster comprises 20 respondents, or 7.3%. All members fall under the "other functions" category, hold a high school diploma or equivalent, and are at the staff level. A total of 85.0% are aged 25–30. This profile captures B2B professionals who are not in core commercial or operational functions but are still involved in coordination with business partners.

Work experience of 2–5 years is the dominant category across all clusters, ranging from 84.8% to 93.3%; these results help characterize the sample but are not the primary differentiators between profiles. A combination of job field, education, age, and job title primarily drives cluster differentiation.

External Validation and Hypothesis Evaluation

External validation shows that cluster profiles are not randomly distributed across organizational and market contexts (Table 6). Differences in distribution were found based on company size, industry, and type of primary partner. The strength of the relationships ranged from small to moderate. Gender also showed exploratory differences in distribution, while operational region did not differ significantly.

Table 6. Results of external cluster validation

External Variables	n	χ^2	df	p	Cramer's V	Results
Company size	273	31,274	8	<0.001	0.239	Significant
Industry	273	72,073	16	<0.001	0.257	Significant
Partner type	212	32,402	12	0.001	0.226	Significant
Gender	273	31,434	4	<0.001	0.339	Significant
Operational area	273	16,932	12	0.152	0.144	Not significant

Table 7. Summary of Hypothesis Evaluation

Hypothesis	Focus	Analytical evidence	Conclusion
H1	The existence of distinct profiles	Five substantively distinct profiles; moderate silhouette	Supported on an exploratory basis

H2	Differences based on company size	χ^2 (8) = 31.274; p < 0.001; V = 0.239	Supported
H3	Differences by industry	χ^2 (16) = 72.073; p < 0.001; V = 0.257	Supported
H4	Differences by Partner Type	χ^2 (12) = 32.402; p = 0.001; V = 0.226; n = 212	Supported
H5	Convergence of TwoStep and K-Modes	Agreement 66.3%; ARI = 0.370; NMI = 0.484	Partially supported

A summary of the hypothesis testing is presented in Table 7. H1 is considered supported at an exploratory level because the five profiles show distinct dominant category patterns and can be interpreted in the context of B2B marketing. The chi-square results support H2, H3, and H4. H5 is only partially supported because the convergence is at a moderate level, not a high one. These findings indicate that the profile structure is sufficiently consistent for preliminary interpretation but still needs to be tested on other samples or through resampling procedures.

Discussion

The research findings confirm that B2B relationship practitioners cannot be treated as a homogeneous workforce. The identified profiles reflect different combinations of job functions, education, career stages, and levels of organizational authority, encompassing operational relationship professionals, early-career commercial staff, highly educated commercial staff, commercial supervisors, and support function staff. These patterns expand the scope of B2B segmentation studies, which have traditionally focused more on customers and buyer companies. The research findings also reinforce the boundary-spanning perspective, as value creation in B2B markets depends not only on marketing and sales personnel but also on operational and support functions that translate commercial promises into services, coordination, and problem-solving.

Differences in profiles based on company size, industry, and type of primary partner indicate that the configuration of B2B relationship actors is embedded in the organizational and market context. Large companies tend to employ a more specialized division of roles, whereas smaller companies are more likely to rely on employees with broad, multifunctional responsibilities. Industry characteristics also influence the involvement of commercial, operational, technical, and logistics functions, as each industry has different product complexities, service needs, and channel structures. Similarly, relationships with suppliers, distributors, retailers, business customers, or intermediaries require different forms of communication, negotiation, and operational coordination. Therefore, the composition of the B2B relationship management team needs to be tailored to the company's structure and the characteristics of its business network.

From a methodological perspective, the combination of Two-Step Cluster Analysis and K-Modes provides a useful approach for identifying and validating profiles based on categorical data. Two-Step Cluster Analysis helps explore group structures, while K-Modes clarifies the dominant characteristics of each profile. However, the resulting profiles should still be understood as exploratory classifications rather than universal categories. From a managerial perspective, these findings suggest that companies should avoid implementing a one-size-fits-all approach to employee development. Training programs, career development, delegation of authority, and cross-functional coordination must be tailored to the characteristics and needs of commercial, operational, supervisory, and support staff involved in B2B relationships.

CONCLUSION AND SUGGESTIONS

Conclusion

This study identifies five profiles of B2B relationship practitioners in Indonesia: operational relationship professionals, early-career commercial staff, highly educated commercial staff, commercial supervisors, and support function staff. Differences among these profiles are primarily shaped by job function, educational background, age, and position level. The external validation results further indicate that cluster distributions vary according to company size, industry, and type of primary business partner. These findings demonstrate that B2B relationship management involves individuals across diverse organizational functions and career levels rather than being limited to marketing and sales personnel. Self-expression value through customer engagement does not have a significant effect on customer loyalty. This finding indicates that customer loyalty is formed more directly through the congruence between customer identity and café image than through the process of customer engagement.

Limitations

This study employed purposive sampling, and the respondents were predominantly young, staff-level employees from the Greater Jakarta area. Consequently, the generalizability of the findings to the broader population of B2B relationship practitioners in Indonesia remains limited. Moreover, the silhouette coefficient and the convergence between the TwoStep and K-Modes solutions were moderate. Therefore, the proposed five-cluster solution should be interpreted as exploratory. The consolidation of several job categories may have also reduced the level of detail captured regarding differences among specific

Recommendation

Future studies should employ broader, more geographically diverse, and more balanced samples across age groups, organizational levels, industries, and company sizes. The five-cluster solution should also be validated using an independent sample and compared with alternative techniques, such as Latent Class Analysis and other clustering methods. In practice, companies can use these profiles to develop more targeted approaches to training, staffing, career development, and cross-functional coordination according to the characteristics and needs of each group of B2B relationship practitioners.

Author Contribution

The first author contributed to the conceptualization, methodology, investigation, data collection, formal analysis, visualization, and preparation of the original manuscript. The second author contributed to the conceptualization, methodological development, validation, supervision, and critical review and editing of the manuscript. The third author contributed to the validation and interpretation of the findings, supervision, and critical review and editing of the manuscript. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for the accuracy and integrity of the work.

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