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| RESEARCH ARTICLE

Understanding Insurance Uptake in the Philippines: A Cluster-Based Analysis of Consumer Priorities

Emmanuel Paulino, DBA, LPT[1] ✉ **Djhoana M. Rington, PhD, MBA, LPT, CGSP, CHRA**[2], **Noemi C. Gocuyo, MGM, LPT**[3], **Lalaine A. Isip**[4], **Ronald P. Romero, Ph.D**[5], **Ronaldo A. Tan, Ph.D.**[6] and **Paulo Noel A. Mazo, DBA, LPT**[7]

[1]*Ateneo de Manila University, De La Salle University, University of the City of Manila, Jose Rizal University, and San Beda College Alabang*
[2]*College of Business Administration and Accountancy, De La Salle University Dasmarinas. Marketing Department. DBB-B 4115 West Ave., Dasmariñas, Cavite*
[3456]*Pamantasan ng Lungsod ng Maynila (PLM), General Luna corner Muralla St., Intramuros Manila, Philippines*
[7]*Assistant Professor III at the College of Business Administration in Pamantasan ng Lungsod ng Maynila (PLM).*
Corresponding Author: Emmanuel Paulino, **E-mail**: eppaulino@dlsud.edu.ph

| ABSTRACT
Despite growing financial awareness, insurance uptake in the Philippines remains low compared to peer economies. This study explores the perceptions and behaviors of Filipino policyholders to identify actionable insights for increasing insurance adoption. The research aims to segment policyholders based on demographic, psychographic, and investment behavior variables, providing a nuanced understanding of consumer priorities and guiding more effective industry strategies. Using a quantitative approach, data were collected from insurance policyholders aged 18 and above in Metro Manila through stratified sampling to ensure demographic representation. A minimum sample of 180 respondents was determined for cluster analysis. The analysis revealed three distinct market segments: those who value service quality and accessibility, those focused on coverage, and those seeking basic, low-risk options. Each cluster exhibits unique demographic and behavioral traits. Findings offer valuable guidance for insurers to tailor marketing, product design, and customer engagement strategies, ultimately fostering trust and boosting insurance participation across different Filipino market segments.

| KEYWORDS

Insurance, Investment behavior, ANOVA, Cluster analysis, Insurance, Financial Awareness.

| ARTICLE INFORMATION

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1. Introduction

Despite growing financial awareness among Filipinos, insurance uptake in the Philippines remains significantly lower than in peer economies. Structural barriers such as limited financial literacy, perceived complexity of insurance products, affordability concerns, and low trust in insurance providers continue to hinder the industry's growth (Eling, 2024; Gatzert, Reichel, & Zitzmann, 2020). While economic volatility, climate-related risks, and increased digitalization have heightened the relevance of insurance, many Filipinos still view it as non-essential or inaccessible (Eling, 2024; Kaffash, Azizi, Huang, & Zhu, 2020).

The Philippine insurance industry is now at a critical juncture, challenged to modernize its offerings, engage diverse consumer segments, and promote financial inclusion. Leveraging digital tools, personalized product lines, and data analytics has become increasingly essential to the industry's growth (Sood et al., 2022; Kar & Navin, 2021). Yet, existing segmentation approaches are often limited to basic demographic profiling, failing to capture the full complexity of policyholders' motivations, preferences, and risk attitudes (Bohnert, Fritzsche, & Gregor, 2019).

This study explores the perceptions and behaviors of Filipino policyholders to identify actionable insights for increasing insurance adoption. It employs cluster analysis to segment consumers based on demographic, psychographic, and investment behavior variables—enabling a more nuanced understanding of consumer priorities. The insights derived from these clusters can inform targeted strategies for product development, marketing, and policy advocacy (Bohnert, Fritzsche, & Gregor, 2019; Sood et al., 2022).

Reviewing current studies reveals that the use of cluster analysis in understanding policyholder behavior, particularly regarding Valuation by Policyholders and Investment Behavior, is still limited (Higuchi & Maehara, 2021; Yukselturk & Top, 2013; McCarthy et al., 2016). While existing research focuses on broad demographic segmentation, such as age, gender, and digital engagement (Zhao et al., 2020; Müllensiefen et al., 2018; Sakolwitayanon et al., 2018), there is a lack of emphasis on the nuanced factors that influence valuation preferences and investment behavior. For instance, while Kramarić et al. (2018) and Omar et al. (2021) have explored clustering based on premium preferences and risk tolerance, the role of more intricate factors such as insurance literacy, financial knowledge, and personal control beliefs in shaping Valuation by Policyholders remains underexplored (O'Connor & Kabadayi, 2020). Additionally, the impact of cognitive and ethical dimensions on investment behavior, as suggested by Awad et al. (2018), has not been fully integrated into cluster analysis models, highlighting the need for a broader perspective on policyholder behavior. Similarly, research by Ma et al. (2021) and Kovács et al. (2021) on investment behavior within clusters suggests that financial behavior can vary significantly, but the influence of macroeconomic factors like interest rates (Ozdagli & Wang, 2019) and contextual elements (Makalani, 2022) complicates predictions based solely on internal segmentation variables.

This study aims to explore the perceptions and behaviors of Filipino policyholders through the lens of demographic, psychographic, and investment behavior variables. By utilizing cluster analysis, the research seeks to uncover actionable insights that can guide targeted marketing, product development, and policy advocacy. The findings will help insurers better understand the distinct preferences and risk attitudes of different consumer segments, potentially improving adoption rates and fostering financial inclusion within the Philippine insurance sector.

This study, therefore, aims to bridge these gaps by utilizing cluster analysis to examine the complex interplay of Valuation by Policyholders and Investment Behavior, providing deeper insights into the factors influencing the decision-making processes of Filipino policyholders in the insurance sector.

2. Review of Related Literature

2.1 Valuation by Policyholders

Valuation by policyholders refers to the personal assessment and perceived worth that policyholders assign to an insurance policy based on its ability to meet their specific needs, expectations, and preferences. It reflects how policyholders subjectively evaluate the benefits, reliability, and fairness of insurance offerings, considering both tangible factors such as financial returns and service quality, and intangible factors like trust, satisfaction, and belief in the insurer. Ramyashree (2024) emphasized that policyholders' preferences are shaped by their awareness, expectations, and the perceived usefulness of the policy, while Bhatia et al. (2024) demonstrated how policyholders' beliefs influence their decisions to continue or lapse in their insurance coverage. This highlights that valuation is inherently linked to individual psychology, preferences, and the level of satisfaction derived from policy features and services.

Academic literature has increasingly analyzed how valuation by policyholders is impacted by heterogeneity in preferences, time perception, and strategic behaviors. Boonen and Liu (2022) and Bernard et al. (2018) explored how insurance products must account for different risk preferences among policyholders, which affect how individuals value insurance contracts. Ghossoub and Zhu (2024) further extended this by introducing Stackelberg equilibria, showing that insurers anticipate diverse policyholder behavior when designing optimal contracts.

Similarly, Apicella et al. (2025) pointed out that subjective beliefs about insurers—especially in the context of environmental, social, and governance (ESG) concerns—can become new drivers of reputational risk and influence how policies are valued. Wei et al. (2024) incorporated time preference variability into mutual insurance models, reinforcing the idea that valuation is dynamic and varies among individuals. These findings reveal that valuation is not only an economic evaluation but also a behavioral outcome rooted in complex, evolving individual and social factors.

Valuation by policyholders is closely related to four key sub-variables: coverage, accessibility, premium, and quality of service. Coverage refers to the extent and comprehensiveness of protection offered, which influences how much value policyholders place on the policy—those perceiving broader and clearer coverage tend to assign higher valuation (Ramyashree, 2024; Muthusamy & Yuvarani, 2021). Accessibility, including ease of enrollment and information availability, further affects perceived value; policyholders are more likely to value policies they can easily understand and access (Islam et al., 2021).

Premium levels also play a critical role, as cost-benefit assessments shape value perception—high premiums may lower perceived value unless matched by perceived quality or benefits (Boonen & Jiang, 2024). Lastly, quality of service—such as responsiveness, transparency, and support—directly impacts policyholder satisfaction and consequently their valuation of the insurance provider (Kaliyammal & Mohanasundaram, 2025). Therefore, valuation is an integrated outcome of both product features and customer experience, mediated by individual beliefs, preferences, and satisfaction levels.

2.2 Investment Behavior

Investment behaviour refers to the decision-making processes and actions taken by individuals or institutions when allocating capital in various investment instruments. This behaviour encompasses how investors choose assets, assess risk, react to market signals, and adapt to changing economic and policy environments. According to Kurniawati et al. (2022), factors such as financial understanding, risk perception, and prior investment experience significantly influence how investors behave. Similarly, Hastings and Mitchell (2020) revealed that financial literacy and psychological traits, such as impatience, shape both the quality and quantity of investment decisions, particularly in retirement planning. Investment behaviour, therefore, reflects both rational analysis and behavioral influences rooted in cognition, emotion, and socio-economic context.

Various studies demonstrate that investment behaviour is also shaped by external conditions, institutional environments, and cultural or ethical values. Zhang et al. (2020) and Qiu et al. (2021) showed how environmental regulations influence foreign investors' behaviour, with significant impacts on sustainability and productivity outcomes. In the realm of corporate finance, Ljungqvist et al. (2020) highlighted the systematic strategies used by buyout funds, while Bhuiyan and Hooks (2019) observed how governance issues, such as problematic directors, can lead to over-investment.

Cultural and social factors also play a role—Lee et al. (2019) found that local culture can trigger speculative tendencies, and Jonwall et al. (2022) emphasized a rising trend toward socially responsible investing among individuals. These perspectives underline that investment behaviour is a dynamic blend of individual agency and external institutional pressures.

Investment behaviour is closely related to two critical sub-variables: volume and frequency of investments. Volume refers to the amount of capital deployed, while frequency relates to how often investments are made. Both serve as key indicators of investor confidence and strategy. Berns et al. (2022) found that shifts in corporate disclosures, particularly the tone of Management Discussion and Analysis (MD&A) sections, significantly predict changes in both the volume and frequency of investor activity. Xi et al. (2019) observed that in the cryptocurrency market, behavioural drivers such as risk appetite and information asymmetry influenced frequent speculative investments. Meanwhile, Kurniawati et al. (2022) demonstrated that higher levels of financial understanding and experience led to increased investment activity both in terms of volume and repetition. The existing literature supports the idea that volume and frequency are tangible reflections of deeper investment behaviour, shaped by a confluence of personal, economic, informational, and cultural factors.

2.3 Hypotheses Development

Higuchi and Maehara (2021), Yukselturk and Top (2013), and McCarthy et al. (2016) all found that variables such as age, gender, education, and digital engagement significantly contribute to distinct cluster formation, which insurers can leverage for targeted marketing and product design. Zhao et al. (2020), Müllensiefen et al. (2018), and Sakolwitayanon et al. (2018) further emphasized that socio-demographics shape consumer behavior, influencing choices such as policy type and coverage level. Cui and Zhang (2024) confirmed spatial and preference-based demographic clustering in urban planning, paralleling segmentation strategies employed in insurance distribution and pricing. However, Awad et al. (2018) provide a contradiction, suggesting that moral and ethical decision-making can diverge from traditional demographic categorizations. This implies that in ethically charged domains like insurance, especially life and health, demographics may not always predict behavior, and reliance on such clustering could overlook key psychological or moral dimensions.

Kramarić et al. (2018) and Omar et al. (2021) utilized cluster analysis to segment insurance customers based on premium preferences, such as affordability, frequency of payment, and risk tolerance. These clusters assist insurers in tailoring pricing models to align with customer willingness to pay. Alt et al. (2021) demonstrated that customer interactions across digital touchpoints also influence clustering, highlighting the role of channel preference in premium selection. Kuhn et al. (2021) validated ideological preferences for insurance models (e.g., private vs. social insurance) as another basis for clustering. However, O'Connor and Kabadayi (2020) pose a partial contradiction, arguing that premium preferences are also driven by internal cognitive factors, such as insurance literacy, financial knowledge, and personal control beliefs. These elements may not align neatly with observable clustering variables, suggesting that behavioral segmentation might require a combination of internal and external factors for accurate classification.

Ma et al. (2021) found that policyholders with chronic health conditions (e.g., diabetes) displayed unique investment and risk aversion behaviors, justifying cluster-based product customization. Strobl (2022) used experimental data to show that perceived background risks significantly influence insurance uptake and investment decisions, while Kovács et al. (2021) revealed that clusters based on financial behavior predict variations in investment strategy. Muthusamy and Yuvarani (2022) also emphasized that loyalty, renewal behavior, and optional investment products vary across policyholder clusters. Nonetheless, Ozdagli and Wang (2019) introduced a contradiction, noting that macroeconomic variables like interest rates can shape investment behavior across all clusters, thus weakening the predictive power of segmentation alone. Makalani (2022) added that both personal traits and contextual influences, such as economic environment or media exposure, contribute to risk perception and behavior. This suggests that while clusters are useful, they may not fully encapsulate the dynamic, multi-level drivers of investment decisions within the insurance industry.

Thus, the following hypotheses are stated:

H1: There is a significant relationship between the formed clusters and the demographic profiles of the respondents.

H2: There are significant clusters that may be formed based on the preference for insurance premium of the respondents.

H3: There is a significant difference in the investment behavior of policyholders' insurance between the clusters.

3. Methodology

3.1 Research Participants and Sampling

The respondents of this study are men and women aged 18 years old and above who reside in Metro Manila and have purchased at least one life insurance policy. They were specifically chosen due to their active participation in the insurance industry as policyholders, which provides them with firsthand experience in premium selection, policy investment, and ongoing insurance-related decisions. Their capacity to regularly pay premiums and maintain life insurance coverage indicates financial involvement and commitment, making them suitable subjects for analyzing behavioral patterns and preferences within the insurance market. Moreover, Metro Manila, being a highly urbanized and economically active region, offers access to a broad demographic with varying levels of insurance literacy, making it ideal for studying how demographic and behavioral clusters influence insurance choices and investment behavior.

3.2 Instrumentation

The survey questionnaire was used to collect data with two main parts, the demographic profile and the Likert scale items. A 4-point Likert scale assessed the respondents' preferences and behavior from 1 as Strongly Disagree to 4 as Strongly Agree.

Likert scale items were modified statements from existing literature to measure each of the variables of the study: Valuation by Policyholders (Ramyashree, 2024; Ghossoub & Zhu, 2024), Investment Behavior (Bhuiyan & Hooks, 2019; Berns et al., 2022)

Table 1. Construct and Indicators

Construct	Indicators
Valuation by Policyholders	I find my insurance easy to access in my area I find my insurance accessible in every health institution I find insurance accessible in every financial institution I prefer lower premiums for my insurance with corresponding low coverage. I find my insurance premium reasonable for my coverage I would describe my insurance premium to be a large portion of my income. I am satisfied with my insurance provider's quality of service The customer service is accommodating when I find things difficult Customer service invests time in providing quality support to its clients The customer service responds in a timely way
Investment Behavior	Annually, your insurance premiums amount to (In PHP) 1 to 4,000 4,001 to 8,000 8,001 to 12,000 12,001 to 16,000 16,001 and up In what intervals do you pay for your insurance premiums Monthly Bi-monthly Quarterly Semi-Annually Annually

Validity and reliability tests were conducted using confirmatory factor analysis and composite reliability. Items that failed such tests were either removed or modified.

3.3 Statistical Analysis of Data

K-means cluster analysis was employed to identify groups of respondents with similar psychographic preferences. This analysis was conducted using the Lloyd algorithm, with the number of initial random starting values set to 10, following the approach of Ostrovsky et al. (2013). The optimal number of clusters was determined based on the criteria suggested by Chowdhury et al. (2021). The resulting clusters exhibit external homogeneity, meaning that individuals within each cluster share common characteristics; however, they also display internal heterogeneity, as the subpopulations within each cluster differ in composition and underlying traits.

4. Results

Figure 1. Optimal Number of Clusters

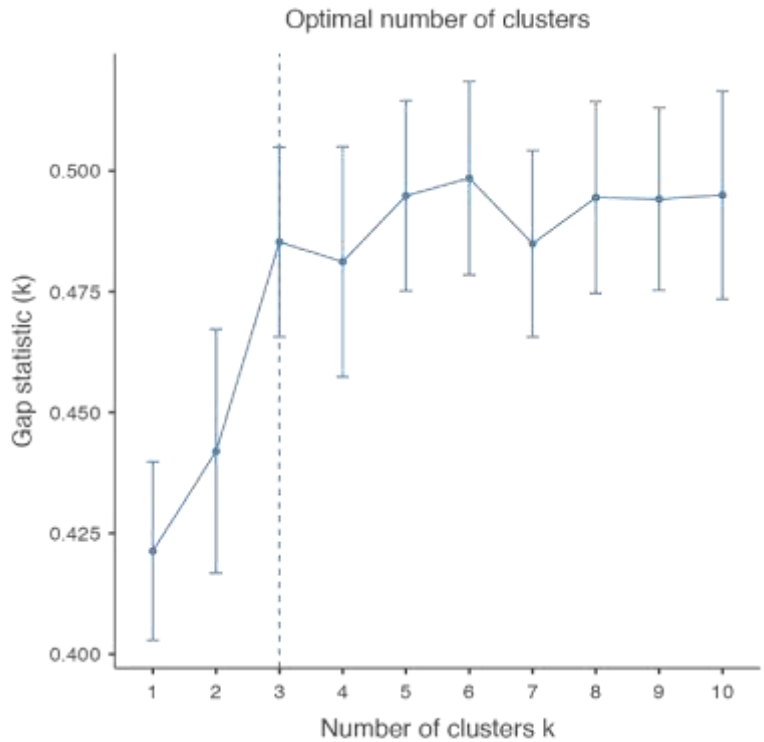

Figure 1 presents a Gap Statistic plot used to identify the optimal number of clusters for K-means clustering. The x-axis shows the number of clusters (k) evaluated from 1 to 10, while the y-axis displays the corresponding Gap Statistic values. The Gap Statistic compares the total within intra-cluster variation for different values of k with their expected values under a null reference distribution. In this plot, the highest point before the error bars begin to overlap significantly is at k = 3, which is also marked by a vertical dashed line indicating the optimal number of clusters. This suggests that segmenting the dataset into three clusters yields the most appropriate balance between within-cluster compactness and between-cluster separation. Therefore, the analysis proceeds with three clusters, as this configuration provides meaningful groupings while avoiding overfitting and maintaining interpretability.

Table 1. Sum of Squares Table

	Value
Cluster 1	76
Cluster 2	139.6
Cluster 3	57
Between clusters	328.5
Total	601

Table 1 shows the variance distribution from a K-means clustering analysis involving three clusters. Cluster 1, Cluster 2, and Cluster 3 have within-cluster sum of squares values of 76, 139.6, and 57, respectively, which reflect how compact or tightly grouped the data points are within each cluster. Lower values indicate greater internal consistency among members of a cluster. The between-cluster sum of squares is 328.5, representing the amount of variance due to differences between the clusters. This is a key indicator of how distinct or well-separated the clusters are from each other. The total sum of squares across the dataset is 601, and by comparing the between-cluster variance to the total variance, it is evident that approximately 54.65% of the total variance is explained by the separation among the clusters. This suggests that the clustering model is effective in distinguishing meaningful groupings, as more than half of the variation in the data is captured by the three-cluster solution. This outcome aligns with the earlier Gap Statistic result, which identified three as the optimal number of clusters.

Table 2. Centroids of Clusters Table

Cluster No	Count	Coverage	Accessibility	Premium	Quality	Cluster Name
1	83	1.253	4.502	4.056	4.524	High Features
2	54	3.722	4.185	3.513	4.194	Coverage Focused
3	45	1.222	3.526	3.096	3.378	Safe Players

Table 2 presents the summary of three distinct clusters derived from K-means clustering based on respondents' preferences toward various insurance product attributes—specifically coverage, accessibility, premium, and quality. Cluster 1, labeled High Features, is the largest group with 83 respondents. This cluster shows a strong preference for high accessibility (4.502) and quality (4.524), alongside relatively high ratings for premium affordability (4.056), but low importance placed on coverage (1.253). Cluster 2, labeled Coverage Focused, consists of 54 respondents who highly value coverage (3.722) more than any other cluster, while still rating accessibility (4.185) and quality (4.194) positively, though they show less concern for premium affordability (3.513). Cluster 3, labeled Safe Players, includes 45 respondents and reflects the most conservative profile, assigning low to moderate scores across all attributes—coverage (1.222), accessibility (3.526), premium (3.096), and quality (3.378). This suggests a cautious attitude toward insurance decisions, possibly prioritizing stability over aggressive feature selection. The differences across these clusters highlight varying market segments in the insurance industry, indicating the need for tailored insurance offerings to match distinct consumer psychographic profiles.

Table 3. One-Way ANOVA (Welch's)

Variables	F	df1	df2	p
Coverage	213.4	2	96.4	< .001
Accessibility	32.9	2	87.1	< .001
Premium	50.9	2	102	< .001
Quality of Service	65.8	2	88.5	< .001

The table presents the results of Welch's ANOVA, which was used to test for significant differences across the three identified clusters in terms of four key insurance product variables: coverage, accessibility, premium, and quality of service. Since Welch's ANOVA does not assume homoscedasticity (equal variances), it is appropriate for datasets where variance across groups may differ. The results show statistically significant differences in all four variables among the clusters, with p-values less than .001 in each case, indicating strong evidence against the null hypothesis of equal means. Specifically, coverage shows the most substantial difference (F = 213.4, df1 = 2, df2 = 96.4), suggesting that respondents across clusters prioritize this factor very differently.

Significant differences were also observed in quality of service (F = 65.8), premium (F = 50.9), and accessibility (F = 32.9), all with respective degrees of freedom noted. These findings confirm that the clusters not only represent statistically distinct groups in terms of psychographic preferences but also differ meaningfully in how they value specific insurance attributes. This underscores the relevance of segment-based strategies for insurance companies aiming to address diverse consumer needs.

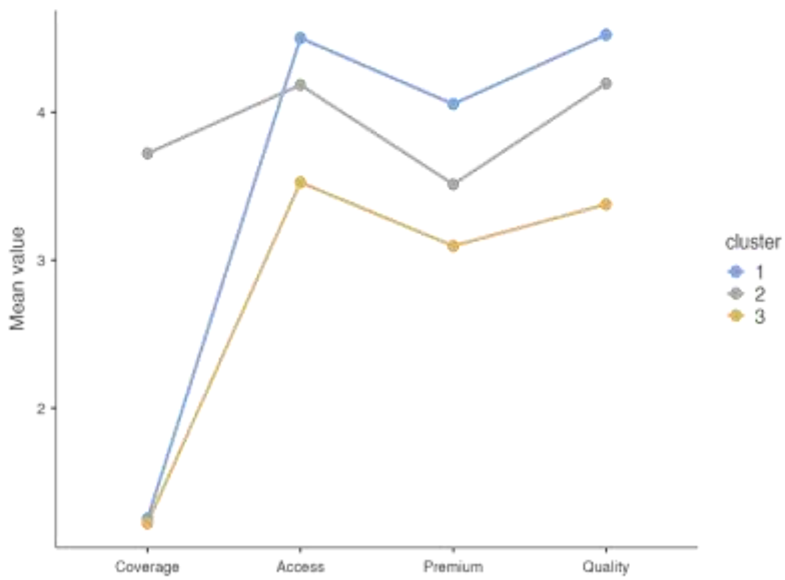

Figure 2. Plot Means Across Clusters

Figure 2 shows the line plot, which reveals three distinct clusters of insurance buyers based on their mean values across the attributes of Coverage, Accessibility, Premium, and Quality.

For Cluster 1, represented by the blue line, the mean values remain consistently high across all attributes, particularly excelling in Accessibility and Quality. These high values suggest a segment that highly values comprehensive insurance features. The relatively stable trend throughout the attributes highlights the consistent preferences of this group, which is named "Comprehensive Seekers" due to their focus on broad coverage and superior service quality.

Moving to Cluster 2, depicted by the gray line, the mean values for Coverage are the highest among the three clusters, although scores for Accessibility, Premium, and Quality are somewhat moderate in comparison. This indicates a group that prioritizes extensive coverage, even if other factors such as Premium and Quality are slightly lower. This cluster is named "Coverage Prioritizers" due to its strong emphasis on the breadth of coverage over other insurance features.

For Cluster 3, illustrated by the orange line, the mean values are the lowest across all attributes. This cluster shows a cautious approach, with lower preferences in Coverage, Accessibility, Premium, and Quality. The consistent low scores across these attributes reflect a more conservative attitude towards insurance. This group is named "Safe Players" due to their more cautious and reserved preferences in choosing insurance products.

The distinct separation between the three lines reinforces the differing preferences and priorities of each cluster, supporting targeted marketing and product customization strategies in the insurance industry.

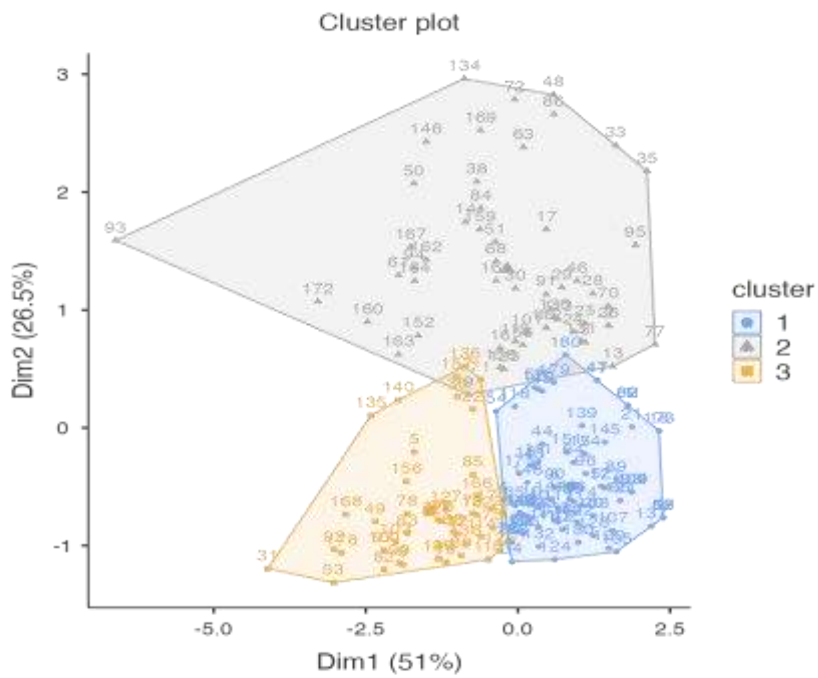

Figure 3. Clusters Plot

The cluster plot above illustrates three distinct groupings of data points derived from an analysis relevant to the insurance industry. These clusters, formed based on key dimensions of variation (Dim1 and Dim2), may represent different profiles or segments within the insurance business—such as customer behavior patterns, policyholder demographics, or organizational performance metrics across insurance firms.

Cluster 1 (blue) could correspond to a segment of insurance firms or customers that exhibit strong performance indicators, possibly characterized by high levels of digital adoption, customer satisfaction, and efficient claims processing. The compact nature of this cluster suggests that members share closely aligned characteristics, which may point to well-established practices or homogeneous market conditions.

Cluster 2 (gray) is more widely spread out, implying diversity within this segment. This group might include traditional insurance firms or customers with mixed engagement levels—perhaps those undergoing digital transformation or facing operational inefficiencies. The variability suggests a transitional or fragmented profile that could benefit from targeted interventions or modernization strategies.

Cluster 3 (orange), while also relatively distinct, may represent a niche segment—such as smaller insurance providers or high-risk customer groups, with specific operational or behavioral attributes. These could include firms with specialized products, limited technological investment, or unique market positioning.

Table 4. ANOVA of Investment Behavior

	Sum of Squares	df	Mean Square	F	p	η^2
Clusters	22.5	2	11.235	13.4	< .001	0.13
Residuals	149.9	179	0.837			

The ANOVA results reveal significant differences in the dependent variable across the three clusters. The sum of squares for Clusters is 22.5 with 2 degrees of freedom, resulting in a mean square of 11.235. The residual sum of squares is 149.9 with 179 degrees of freedom, yielding a mean square of 0.837. The resulting F statistic is 13.4, with a p value of less than .001, indicating a statistically significant difference among the clusters, $F(2, 179) = 13.4$, $p < .001$. The effect size ($\eta^2 = .13$) suggests that 13% of the variance in the dependent variable can be attributed to differences between the clusters, representing a medium effect size according to conventional benchmarks. This finding suggests meaningful variation across the cluster groups.

5. Discussion, Implications, and Limitations

5.1 Discussion

This study identified three distinct clusters of insurance policyholders—High Features, Coverage Focused, and Safe Players—each demonstrating unique preferences across key insurance attributes. The High Features cluster (Cluster 1), the largest group with 83 respondents, expressed the strongest preferences for service-related features, scoring highest in accessibility (M = 4.502), satisfaction with premiums (M = 4.056), and quality of service (M = 4.524), but lowest in coverage (M = 1.253). This suggests a consumer segment that values convenience and service excellence more than comprehensive protection. The Coverage Focused cluster (Cluster 2), with 54 respondents, prioritized insurance coverage (M = 3.722) above all, while maintaining relatively favorable views on accessibility and quality, and moderate satisfaction with premiums. This group reflects consumers who are protection-driven, seeking broad policy coverage even if it comes at a cost. Meanwhile, the Safe Players cluster (Cluster 3), the smallest with 45 respondents, consistently rated all attributes lowest, particularly coverage (M = 1.222), implying a conservative, cost-sensitive segment that likely engages minimally with insurance features and benefits.

Statistical analyses validated these distinctions. Welch's ANOVA, which does not assume equal variances, confirmed significant differences across clusters for all four insurance attributes: coverage ($F = 213.4$, $p < .001$), accessibility ($F = 32.9$, $p < .001$), premium ($F = 50.9$, $p < .001$), and quality of service ($F = 65.8$, $p < .001$). Furthermore, the overall cluster differences were reinforced by additional ANOVA results. The sum of squares between clusters was 22.5 (df = 2), with a mean square of 11.235, and a residual sum of squares of 149.9 (df = 179), resulting in an F statistic of 13.4 and a p-value of < .001. This confirms statistically significant variation among clusters, $F(2, 179) = 13.4$, $p < .001$. The effect size ($\eta^2 = .13$) indicates that 13% of the variance in the dependent variable is explained by cluster membership—a medium effect size by conventional standards.

5.2 Conclusion

The results reveal three distinct types of insurance policyholders, each exhibiting unique priorities and engagement levels with insurance services. The High Features group values service quality, accessibility, and premium satisfaction above comprehensive coverage, indicating a consumer segment that prioritizes convenience and experience over the breadth of protection. The Coverage Focused group is primarily driven by the extent of insurance coverage, reflecting a preference for policies that offer wide-ranging protection even if premium costs are moderately high. In contrast, the Safe Players are the most conservative, showing the lowest ratings across all attributes, which suggests minimal engagement and a likely emphasis on affordability and simplicity over expansive features.

These findings highlight the presence of clear, behaviorally distinct segments within the insurance market, offering crucial insights into how different groups evaluate and interact with insurance products. This segmentation is valuable for insurers and marketers, as it enables the development of tailored strategies that align with the specific needs, preferences, and motivations of each policyholder type. By understanding these consumer profiles, companies can enhance customer satisfaction, improve retention, and drive strategic growth in the increasingly competitive insurance industry.

5.3 Implications

The practical implications of this study offer valuable insights for insurance companies, policyholders, and marketing strategists operating within the insurance industry. The identification of three distinct clusters—High Features, Coverage Focused, and Safe Players—provides a framework for targeted strategy development in product design, pricing, and customer relationship management.

For insurance companies, understanding that the High Features cluster values accessibility, premium quality, and service allows firms to focus on high-tier product offerings, potentially including add-on benefits, loyalty rewards, or concierge services. The Coverage Focused group, which emphasizes coverage above all, may respond best to policies that maximize protection and transparency while minimizing non-essential features, allowing insurers to design simple, robust packages tailored to risk-averse consumers. Meanwhile, the Safe Players, who show the lowest preference across features, represent a more cautious market segment. Insurers might attract this group by emphasizing affordability, basic coverage, and trust-building mechanisms such as guarantees or strong customer support.

For policyholders and potential insurance buyers, the findings suggest that insurers are increasingly capable of responding to specific customer needs. Consumers may experience more personalized offerings, more relevant policy recommendations, and improved satisfaction as company's leverage segmentation insights to enhance client engagement. This tailored approach could also help address policy lapses by ensuring buyers feel their premiums are matched with adequate service and protection.

Marketing strategists and business planners can use these insights to design targeted campaigns and outreach efforts. For example, digital marketing initiatives can highlight different aspects of a policy—features, coverage, or reliability—depending on the profile of the intended segment. Educational content and promotions can also be customized, such as emphasizing the value of comprehensive insurance for the Coverage Focused or offering trial insurance products to gradually build trust with the Safe Players. These differentiated strategies help reduce churn and promote long-term loyalty.

5.4 Limitations of the Study

A limitation of this study is that it relies on self-reported data to cluster insurance consumers based on their preferences for features such as coverage, accessibility, premium, and service quality. Self-reporting may introduce social desirability bias, where respondents could exaggerate or downplay their actual behaviors or attitudes toward insurance products. Moreover, the findings are specific to insured individuals residing in Metro Manila, which may limit the generalizability of the results to consumers in other regions or countries with different socioeconomic, regulatory, or cultural contexts. The clustering methodology also captures only a snapshot of consumer preferences and does not fully account for other potentially influential variables such as income level, past claim experiences, or financial literacy, which may offer a more holistic view of consumer behavior within the insurance industry.

Statements and Declarations

Ethics Approval and Consent to Participate: Before data gathering, the study underwent evaluation under the Ethics Review of a University in the Philippines. Necessary changes were made upon the review board's recommendation before the survey instrument was disseminated. Before answering the survey, each respondent should complete the Informed Consent form.

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Conflicts of Interest: The authors declare no conflicts of interest

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