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A Study on the Effectiveness of Different Customer Segments (Age, Income, Occupation) in Policy Purchase

Jayesh Chavan[1], Prof. Dr. Vishal Dilip Chavan[2], Dr. Rajat Gera[3]
MBA (Marketing & Sales),– Amity Business School, Amity University Mumbai, Maharashtra, India[1]
Assistant Professor & Project Guide – Amity Business School, Amity University Mumbai, Maharashtra, India[2]
Professor, HOI – Amity Business School, Amity University Mumbai, Maharashtra, India[3]

Abstract : *Customer segmentation is a central tool of marketing management, but its value depends on whether the chosen variables explain differences in customer response and can be converted into action. Drawing on a Summer Internship undertaken as a Marketing Intern at Aspire Consultants from 30 June to 30 August 2026, this paper examines the effectiveness of three demographic segmentation variables – age, income and occupation – in relation to policy purchase. A descriptive and analytical cross-sectional design is adopted, grounded in the segmentation, consumer-behaviour and marketing-research literature. Because verified customer-level records were not available for reproduction, the proposed measures (segment share, enquiry rate, purchase rate and conversion gap) are demonstrated on an illustrative dataset that is clearly labelled as such and does not represent the actual customer portfolio of Aspire Consultants. In the illustration, enquiry rates rise from 42% in the 18–25 group to 74% in the 36–45 group and purchase rates from 18% to 39%, while the largest group (26–35) is not the highest-converting one. Illustrative purchase interest also rises with income (38% to 79%) and is higher among professionals (76%) and salaried customers (69%) than among students (31%). The analysis indicates that age, income and occupation are useful starting points but incomplete explanations, and that segment effectiveness should be judged across reach, response, conversion, value, stability and actionability, supported by sound data quality. A segment-wise communication and measurement framework is proposed, together with a roadmap for validating the findings on authorised customer data.*

Keywords: Customer Segmentation, Age, Income, Occupation, Policy Purchase, Purchase Interest, Segment Effectiveness, Aspire Consultants

I. INTRODUCTION

Markets are rarely homogeneous. Customers differ in their needs, financial resources and ways of evaluating an offer, and mass marketing that treats them alike tends to produce messages that are relevant to few of them. Customer segmentation addresses this problem by dividing a broad market into smaller groups that can be analysed and approached more specifically. The issue is particularly important for policy products, where purchase is a high-involvement decision. A customer may weigh premium, coverage, benefits, exclusions, trust in the provider, claim-related expectations and long-term affordability before committing, and these considerations do not carry the same weight for every individual.

Age, income and occupation are among the most observable demographic characteristics and therefore a practical starting point for segmentation. Age can act as a proxy for life stage and protection needs, income influences the feasible premium range and tolerance for additional benefits, and occupation may signal income stability, financial priorities and preferred channels of communication. Yet a segment is useful only when it leads to a different marketing

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action. If two groups share the same needs, message, price sensitivity and response pattern, separating them adds complexity without adding decision value. For this reason, this paper treats effectiveness – the ability of a segment to explain differences in customer interest or purchase behaviour and to guide action – as the central question, rather than classification alone.

This research is anchored in the author's Summer Internship as a Marketing Intern at Aspire Consultants, completed online from 30 June to 30 August 2026, as recorded in the organisation-issued completion certificate (Aspire Consultants, 2026). Since the certificate verifies the role, dates and mode of the internship but does not provide a detailed company profile or task log, the paper makes no claims about the internal processes of the organisation. It develops an academic framework around the project topic and demonstrates the analysis on an illustrative dataset. The problem addressed is how customer characteristics can be used to understand differences in policy-purchase interest and to support more focused marketing decisions when communication and follow-up resources are limited.

II. LITERATURE REVIEW

Segmentation entered marketing thought as a response to differences in demand. Smith (1956) distinguished segmentation from product differentiation and described it as a strategy that recognises divergent consumer preferences within a heterogeneous market and adjusts the offering to them. Kotler and Keller (2016) place segmentation within the sequence of segmentation, targeting and positioning (STP) and set out the conditions under which a segment is worth pursuing: it should be measurable, substantial, accessible, differentiable and actionable. Armstrong and Kotler (2017) add a practical view by classifying the common bases of segmentation – geographic, demographic, psychographic and behavioural – and linking them to targeting decisions, while Wedel and Kamakura (2000) provide a methodological treatment of segmentation bases, methods and implementation.

Demographic variables remain the most widely used bases because they are observable and easy to record. Wells and Gubar (1966) proposed the family life cycle as a way of grouping consumers by stage rather than by age alone, which supports the use of age as a proxy for life stage while also warning against treating it as a complete explanation. In policy marketing, income is generally linked to affordability and premium tolerance, and occupation to income stability and financial priorities. These links are plausible hypotheses rather than established rules, and they should be tested against observed customer behaviour.

Consumer-behaviour research explains why demographics cannot stand alone. Schiffman and Wisenblit (2019) emphasise that individual differences, perceived need and social influences shape how consumers process information and decide, and Solomon (2018) describes purchase as a process in which personal and situational factors interact with the consumer's level of involvement. Policy purchase is a case in point: the decision may be delayed when perceived need is low, when product information is complex or when trust is insufficient. Yankelovich and Meer (2006) similarly caution that obvious descriptors such as age and income often explain little about why customers choose differently, and that segments should be validated against behaviour.

Together, these sources point to a practical gap. Segmentation principles are widely documented, but a marketer still has to decide, with real data, whether a particular segment is useful: identify it, measure its response, interpret the difference and recommend an action. Malhotra (2019) stresses that such judgements depend on a clear research design, well-defined measures and reliable data. This paper addresses the gap by applying a simple, replicable set of measures to age, income and occupation segments in the context of policy purchase.

III. RESEARCH METHODOLOGY

This study follows a descriptive and analytical, cross-sectional research design (Malhotra, 2019). The descriptive component explains the segmentation framework and the characteristics of the selected groups; the analytical component demonstrates how segment-wise response can be compared and interpreted. A customer or lead record is treated as the unit of analysis, and segments are defined by age (18–25, 26–35, 36–45 and 46+ years), annual income (below □3 lakh, □3–6 lakh, □6–10 lakh and above □10 lakh) and occupation (student, salaried, self-employed and

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professional). The outcomes examined are enquiry, purchase interest and policy purchase, with channel (social, referral, search and direct) recorded as a marketing variable.

A mixed-evidence approach is used. The internship completion certificate provides verified information on the student, the organisation, the role and the internship dates; the marketing literature provides the conceptual foundation; and an illustrative dataset demonstrates the analytical method. The illustrative values were constructed for academic demonstration because authorised customer-level and purchase records were not available for reproduction, and they are labelled as illustrative wherever they appear. The analysis uses spreadsheet-style descriptive measures: segment share (segment customers ÷ total customers × 100), enquiry rate (enquiries ÷ segment leads × 100), purchase rate (purchases ÷ segment leads × 100), conversion gap (segment rate − overall rate), average score and cross-tabulation. Ethically, the framework assumes that customer data are used only with authorisation, that personal identifiers are not reproduced, and that demographic characteristics guide communication relevance rather than justify discriminatory assumptions.

The design carries clear limitations. No verified customer dataset was supplied, so the figures cannot be treated as actual purchase results or tested for statistical significance; the certificate contains no daily task sheet, so specific activities are not claimed; only three demographic variables are examined, leaving geography, family size and prior policy experience outside the core scope; and policy purchase is a multi-factor decision that age, income and occupation alone cannot fully explain.

IV. OBJECTIVES OF THE STUDY

The main objective of this study is to examine how effectively age, income and occupation segment customers in relation to policy-purchase interest, and to translate the observed differences into practical marketing action.

Secondary Objectives: The supporting secondary objectives are as follows:

1. To compare policy-purchase interest and conversion across age segments.
2. To examine income as a segmentation variable by comparing interest and affordability across income bands.
3. To examine occupation as a segmentation variable by comparing response across occupation groups.
4. To assess segment effectiveness using a framework that combines reach, response, conversion, value, stability and actionability.
5. To identify segment-specific communication, follow-up and measurement recommendations.

V. ANALYSIS AND DISCUSSION / ANALYSIS AND INTERPRETATION

This section applies the measures described in Section 3 to the illustrative dataset. All figures in the tables are illustrative: they were prepared to demonstrate the analytical method and are not actual customer, sales or performance data of Aspire Consultants. The interpretations therefore describe what the method would reveal, not what has been observed in the organisation's portfolio.

Table 1: Illustrative Segment Worksheet by Age Group (Total Leads = 480)

Age Segment	Leads (n)	Enquiries (n)	Enquiry Rate (%)	Purchases (n)	Purchase Rate (%)
18–25 years	100	42	42%	18	18%
26–35 years	160	109	68%	52	33%
36–45 years	140	104	74%	55	39%
46+ years	80	44	55%	24	30%
Total / Overall	**480**	**299**	**62%**	**149**	**31%**

Source: Illustrative data prepared for academic demonstration; not actual company/customer data.

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As shown in Table 1, enquiry rates rise from 42% in the 18–25 group to 74% in the 36–45 group before easing to 55% among customers aged 46 and above, and purchase rates follow a similar pattern (18%, 33%, 39% and 30%). Across the 480 illustrative leads, the overall enquiry rate is 62% and the overall purchase rate is 31%. The 26–35 group is the largest, contributing 160 of the 480 leads, yet its purchase rate (33%) is lower than that of the smaller 36–45 group (39%). The pattern therefore illustrates that segment size and segment effectiveness are different things.

Table 2: Illustrative Segment Effectiveness by Age Group (Derived from Table 1)

Age Segment	Enquiry-to-Purchase Conversion (%)	Purchase-Rate Gap vs Overall (pp)	Identified Marketing Role
18–25 years	43%	−13	Awareness and education: test whether affordability or low perceived need limits interest.
26–35 years	48%	+2	Largest lead pool: improve follow-up, as rising financial responsibility may raise perceived need.
36–45 years	53%	+8	Strongest illustrative segment: emphasise family protection and long-term planning.
46+ years	55%	−1	Smaller but converts well once engaged: emphasise trust and benefit clarity.

Source: Illustrative data prepared for academic demonstration; not actual company/customer data. Conversion = purchases ÷ enquiries. Gap = segment purchase rate − overall purchase rate (31%), calculated from the rounded rates in Table 1; pp = percentage points.

Interpretation: Table 2 shows why a single metric can mislead. The 46+ group has a lower enquiry rate (55%) than the 26–35 group (68%), yet it converts the highest share of its enquiries into purchases (55% against 48%). The 18–25 group is weak at both stages, which suggests a different task – building awareness and clarifying need – rather than intensive sales follow-up. Conversion gaps of +8 percentage points for the 36–45 group and −13 for the 18–25 group show where marketing effort could be concentrated or redesigned. These readings are hypotheses to be validated with authorised customer data, not causal claims.

Table 3: Illustrative Purchase Interest by Income Band and Occupation (Interest Score, %)

Dimension	Segment	Illustrative Interest (%)	Possible Marketing Implication
Income	Below ₹3 lakh	38%	Emphasise affordability, basic protection and clarity.
Income	₹3–6 lakh	56%	Test value-focused packages and simple comparisons.
Income	₹6–10 lakh	72%	Explore broader protection and benefit communication.
Income	Above ₹10 lakh	79%	Test premium-value, comprehensive coverage and service positioning.
Occupation	Student	31%	Use short digital content and FAQs that explain early protection.

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Dimension	Segment	Illustrative Interest (%)	Possible Marketing Implication
Occupation	Salaried	69%	Provide clear benefit comparisons and premium-planning content.
Occupation	Self-employed	61%	Stress flexibility, continuity and advisor-led explanation.
Occupation	Professional	76%	Offer convenience, clarity and digital-plus-consultation support.

Source: Illustrative data prepared for academic demonstration; not actual company/customer data.

Discussion: Table 3 shows a rising gradient of illustrative interest from 38% in the lowest income band to 79% in the highest, and a clear difference between occupation groups, with professionals (76%) and salaried customers (69%) ahead of self-employed customers (61%) and students (31%). Income and occupation are likely to overlap with age – students, for example, are likely to be concentrated in the youngest group – so occupation should be retained in a segmentation model only if it adds information after age and income have been considered. Cross-tabulations such as age × income or income × occupation are the logical next step.

Segment profiles explain who the customer is, whereas purchase-factor questions explain why the customer acts. In the illustrative factor mix, the need for protection (28%) and family security (24%) account for just over half of responses, ahead of tax planning (20%), investment (16%) and advisor influence (12%). The illustrative lead-to-purchase conversion index likewise places search (62) and direct (57) ahead of referral (48) and social (36), and an illustrative data-quality audit records 27 exception cases per 100 records, led by missing income (8) and blank occupation (7). Such exceptions can move a customer out of the correct segment and distort segment rates, so data cleaning must precede interpretation.

VI. FINDINGS OF THE STUDY

The key outcomes of the analysis are as follows:

1. Age is a useful but incomplete starting variable: in the illustrative worksheet, enquiry rates rise from 42% (18–25) to 74% (36–45) and ease to 55% (46+), with purchase rates of 18%, 33%, 39% and 30%, but age alone cannot explain why customers differ.
2. Segment size is not segment effectiveness: the 26–35 group supplies the most leads (160 of 480) yet converts at 33%, below the 39% of the 36–45 group.
3. Income and occupation add context: illustrative interest rises from 38% to 79% across income bands and is highest among professionals (76%) and salaried customers (69%), but willingness to buy also depends on dependants, existing cover and perceived risk.
4. Single-stage measures can mislead: the 46+ group has a lower enquiry rate than the 26–35 group but the highest enquiry-to-purchase conversion (55%), so segments must be assessed at more than one stage of the customer journey.
5. Demographics show who, not why: need for protection (28%) and family security (24%) dominate the illustrative purchase-factor mix, and channel conversion differs (search 62, direct 57, referral 48, social 36).
6. Data quality is a precondition for segmentation: missing income, blank occupation, age mismatches, invalid contacts and duplicates (27 exceptions per 100 illustrative records) can distort segment counts and rates.

VII. RECOMMENDATIONS

Drawing from the analysis, the following recommendations are made to marketing teams in policy-related businesses such as Aspire Consultants, to be validated against authorised company data before operational use:

1. Standardise segment definitions and customer data fields. Fix age bands, income categories and occupation labels in

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advance, keep outcome fields (enquiry, purchase) mandatory, apply duplicate checks and record the source and date of each record so that segment reports remain consistent and traceable.

2. Judge segments across the funnel, not by size. Track reach, enquiry, qualified-lead rate, purchase rate, cost per lead and cost per purchase for each segment, and compare each segment with the overall rate (conversion gap).

3. Vary the emphasis of communication, not the facts of the product. Younger customers may need simple explanations and affordability-focused content, middle life-stage customers family protection and planning content, higher-income customers comprehensive value and consultation, self-employed customers advisor-led explanations of flexibility and continuity, and professionals convenient digital-plus-consultation support.

4. Combine demographics with behaviour. Add indicators such as prior enquiry, website interaction, advisor contact and policy awareness, and prioritise follow-up by intent so that effort goes to leads that are ready to move forward.

5. Test before scaling. Compare alternative messages (for example, a protection-focused message against an affordability-focused one) within a defined customer group, period and outcome measure, and review segment performance monthly or quarterly.

6. Use customer data responsibly. Collect only necessary information, restrict access, avoid reproducing personal identifiers in academic material and base decisions on observed behaviour rather than assumptions about individuals.

VIII. CONCLUSION

This paper examined the effectiveness of age, income and occupation as customer-segmentation variables in policy purchase, based on the author's Summer Internship as a Marketing Intern at Aspire Consultants. Using a descriptive and analytical framework demonstrated on a clearly labelled illustrative dataset, it showed that demographic segmentation offers a valuable starting point: age helps structure life-stage analysis, income supports affordability analysis and occupation adds contextual information. At the same time, none of these variables explains policy-purchase behaviour on its own, and the largest segment is not automatically the most effective. The practical value of segmentation lies in linking customer characteristics to measurable outcomes – segment size, enquiry rate, purchase rate, cost and customer value together – and in maintaining clean, consistently defined data. Marketing teams should therefore treat segmentation as a continuing decision-support process that is tested, measured and refined, rather than a one-time classification. Because the figures reported here are illustrative, the findings should be read as a demonstration of method. Future research can apply the framework to an authorised customer dataset covering several months, use statistical tests and logistic regression to examine whether differences across age, income and occupation are significant, add behavioural variables such as prior policy ownership and advisor interaction, and examine whether segment performance remains stable over time.

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