

DATA - DRIVEN DIGITAL MARKETING FRAMEWORK BASED ON CUSTOMER ACQUISITION FOR THE 3D PRINTING INDUSTRY: A CASE STUDY OF TRIDIKU TEKNOKARYA INDONESIA

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ABSTRACT

The 3D printing industry in Indonesia is growing rapidly, yet many SMEs in this sector still run their marketing without leveraging the customer data they already collect. Existing SME digital marketing research remains generic and does not account for the specific attributes of the 3D printing sector, including material diversification, duration-based pricing, and pronounced segment heterogeneity, leaving a significant research gap. This study fills this gap by developing a data driven digital marketing framework based on customer acquisition, consisting of five stages: data collection, segmentation, customer value analysis, strategy selection, and digital marketing execution with content strategy. The framework was validated through a case study at Tridiku Teknokarya Indonesia, a medium scale 3D printing company with 1,484 orders and 401 unique customers from July to December 2025, analyzed via mixed methods combining descriptive statistics with cross tabulation. The novelty lies in five elements: integration of material dimensions and duration-based pricing, use of real transaction data, linking behavior patterns to content strategy, discovery of a custom order effect (80.5% versus 49.5% deal rate), and identification of a revenue concentration paradox (4.9% of orders generating 52.7% of revenue). Theoretically, the study connects purchase intention theory with 3D printing practice through the custom order effect and extends customer profitability distribution theory through the revenue concentration paradox. Managerially, the study recommends structured quotation forms to raise deal rates, budget allocation by segment profitability rather than volume, data driven upsell pathways, and a six phases campaign calendar synchronized with seasonal patterns to help SMEs shift from intuition based to evidence-based marketing.

Keywords: Digital Marketing, Customer Acquisition, 3D Printing, Customer Segmentation, Content Strategy

ABSTRAK

Sektor 3D printing di Indonesia berkembang dengan cepat, namun sebagian besar UMKM di industri ini masih menjalankan pemasaran tanpa memanfaatkan data pelanggan yang telah dikumpulkan. Penelitian ini membangun framework pemasaran digital berbasis data *customer acquisition* yang terdiri dari lima tahap: pengumpulan data, segmentasi pasar, penilaian nilai pelanggan, perumusan strategi, dan implementasi pemasaran digital dengan strategi konten. Validasi dilakukan melalui studi kasus pada Tridiku Teknokarya Indonesia dengan 1.484 *order* dari 401 pelanggan unik selama Juli hingga Desember 2025. Analisis menggunakan metode campuran dengan statistik deskriptif dan *cross tabulation*. Hasil menunjukkan bahwa segmen Mahasiswa mencapai *deal rate* tertinggi sebesar 64,7%

meski hanya menyumbang 26,1% dari total *order*. Segmen Umum menguasai volume terbesar (60,2%) tetapi mencatat nilai *order* median terendah (Rp 60.134). Biaya berbasis durasi mencakup 64 hingga 72% dari total harga di semua segmen. *Order* dengan deskripsi kustomisasi mencatat *deal rate* 80,5% dibandingkan 49,5% untuk *order standar*. Selisih 31 poin persentase ini menandakan *purchase intention* yang tinggi pada pelanggan yang mempersonalisasi permintaan. Penelitian juga menemukan paradoks konsentrasi pendapatan: hanya 4,9% *order* di atas Rp 1 juta menghasilkan 52,7% total *revenue*, dan 20% pelanggan teratas menyumbang 75% pendapatan. Berdasarkan temuan ini, penelitian mengusulkan *content matrix* tujuh tema, empat pilar konten berbasis data, dan kalender kampanye enam fase untuk membantu UMKM bertransformasi dari pemasaran berbasis intuisi ke pemasaran berbasis bukti.

Kata Kunci: Digital Marketing, Customer Acquisition, 3D Printing, Segmentasi Pelanggan, Content Strategy

I. INTRODUCTION

Over the past decade, additive manufacturing, commonly known as 3D printing, has experienced remarkable expansion on a global scale. Wohlers Associates (2024) documented that the worldwide additive manufacturing market reached \$20.035 billion in 2023, reflecting 11.1% growth and breaching the \$20 billion threshold for the first time. Research and Markets (2024) anticipates the market will expand from \$24.9 billion in 2024 to \$176.8 billion by 2034, corresponding to a compound annual growth rate of 21.4%. Markets and Markets (2024) projects a market size of \$37.4 billion by 2029, while Additive Manufacturing Research (2025) estimates growth from \$15.9 billion in 2024 to \$57.8 billion by 2033. This trajectory is propelled by accelerating adoption across healthcare, aerospace, automotive, and consumer goods industries (Protolabs, 2024). Within Indonesia, the 3D printing service landscape is predominantly shaped by SMEs that provide printing solutions to both individual and organizational clients (Holzmann et al., 2020). These enterprises typically manage a handful of Fused Deposition Modeling and resin printers, addressing demands that span from architectural scale models and product prototypes to functional industrial components. Such a heterogeneous customer base poses distinctive challenges for marketing strategy formulation.

According to Kotler and Keller (2016), the efficacy of marketing hinges on a firm's capacity to comprehend its customers, categorize them into meaningful segments, and craft offerings tailored to each segment's requirements. Nevertheless, a considerable number of 3D printing SMEs execute marketing activities without sufficient analytical grounding. The Marketing Centre (2024) reported that 67% of SMEs engage in what they call "marketing in the dark," where budgets are spent without measurement, experiments are run without tracking, and channels are scaled without evidence of effectiveness. Within the 3D printing domain, this behavior manifests as poorly defined target audiences, scattered channel investments, and a lack of awareness regarding customer acquisition cost per channel (ScaleGrowth, 2026). The challenge is compounded by inherent characteristics of the 3D printing industry. There is pronounced material diversity, ranging from budget friendly PLA to premium resin at 14 times the cost per gram. Pricing frameworks are driven primarily by machine time rather than raw material expense. Customer segments are markedly varied, from deadline pressured students to manufacturing firms with recurring part orders.

Prior research has examined digital marketing and customer management as separate domains. Kumar et al. (2026) introduced an Integrated Digital Marketing Framework for SMEs drawing upon Resource Based View, Dynamic Capabilities Theory, and Network Theory. Supriyadi and Pranyoto (2025) formulated a business intelligence driven digital marketing approach for SME market expansion. Jain et al. (2024) investigated pricing mechanisms for 3D Printing as a Service. Holzmann et al. (2020) catalogued business model patterns among 3D printer manufacturers. Pulizzi (2014) traced the development of content marketing as a strategic discipline. Despite these contributions, a notable void persists. Existing SME digital marketing research tends to remain generic, failing to account for the specific attributes of the 3D printing sector, including material diversification, duration-based pricing, and pronounced segment heterogeneity. Meanwhile, 3D printing scholarship has predominantly prioritized technical and operational dimensions over data informed

marketing strategy. To date, no study has systematically woven together customer acquisition data, material preferences, price sensitivity, customer segmentation, and content strategy into a unified framework tailored to the 3D printing industry.

The scientific contribution of this study lies in five elements of novelty. First, the proposed model explicitly incorporates material dimensions and duration-based pricing structures specific to the 3D printing industry, thereby extending SME digital marketing research beyond generic channel selection to include industry specific pricing and material variables. Second, the investigation draws on real customer acquisition records from an operating 3D printing firm rather than relying on simulations or perception-based surveys, providing empirical evidence grounded in actual transaction behavior. Third, the framework links observable customer behavior patterns, including price sensitivity, material choices, seasonality, and customization tendencies, with channel selection and targeted content strategies, thereby forging a connection between analytical insight and marketing execution that has been largely absent from the literature. Fourth, the study documents a custom order effect where orders containing customization descriptions achieve an 80.5% deal rate compared with 49.5% for standard orders, connecting purchase intention theory with 3D printing practice and demonstrating that customization behavior functions as a reliable proxy for purchase intention. Fifth, the research identifies a revenue concentration paradox where a small fraction of orders generates the bulk of revenue while the highest volume segment does not yield the highest per customer profitability, extending customer profitability distribution theory to the 3D printing context. The framework was validated through a case study at Tridiku Teknokarya Indonesia, leveraging a dataset of 1,484 orders from 401 unique customers spanning six months. The study pursues three objectives: (1) construct a data driven digital marketing framework specific to the 3D printing industry; (2) evaluate the framework's applicability at a medium scale 3D printing enterprise; and (3) generate data informed digital marketing and content strategy recommendations for each customer segment.

II. LITERATURE REVIEW

Digital Marketing for SMEs

Chaffey and Ellis Chadwick (2019) characterize digital marketing as the attainment of marketing objectives through the application of digital technologies and media platforms. For SMEs, digital channels present an opportunity to access broader markets at comparatively modest cost. Yet, as Kumar et al. (2026) observed, numerous SMEs deploy digital tools in a fragmented manner without systematic integration, thereby failing to realize synergistic effects. Kotler and Keller (2016) articulated the strategic marketing process across five sequential stages: grasping customer needs, crafting segment-based strategy, constructing marketing programs, cultivating relationships, and capturing customer value. This sequential logic underpins the framework proposed in the present study, where each stage builds upon the analytical output of the preceding one.

Customer Acquisition and Segmentation

Customer acquisition encompasses the process of attracting and converting prospects into paying customers (Salesforce, 2024). In this study, the acquisition process is examined through a sequential funnel: inquiry, deal, repeat, and loyal. Wedel and Kamakura (2012) conceptualized market segmentation as the partitioning of a heterogeneous market into homogeneous subgroups. BusinessConceptor (2024) offered segmentation examples specific to 3D printing enterprises, noting that customer categories in this industry often reflect distinct use cases rather than conventional demographic splits. Within the 3D printing context, effective segmentation extends beyond demographic variables to encompass need categories, material preferences, and purchasing behavior patterns. This multidimensional approach to segmentation aligns with Wedel and Kamakura's (2012) assertion that segmentation schemes should be grounded in behavioral and contextual data when demographic alone prove insufficient.

Pricing Strategy in 3D Printing

Jain et al. (2024) delineated fixed fee and pay per build pricing models for 3DaaS. Sun et al. (2024) investigated pricing approaches for 3D printing platforms, emphasizing the role of platform

dynamics in determining optimal price points. Bi and Wu (2025) analyzed leadership driven pricing and customization within collaborative manufacturing environments, highlighting how customization options influence both pricing and conversion. Hinterhuber (2008) examined customer value-based pricing and the organizational resistance such strategies often encounter, arguing that firms frequently default to cost based pricing even when value-based approaches would yield superior margins. In practical SME 3D printing operations, pricing typically combines material costs calculated by weight with duration costs calculated by print time. This hybrid structure has received limited empirical scrutiny in the academic literature, and the present study addresses this gap by decomposing actual price components across customer segments.

Price Sensitivity and Purchase Intention

Chatterjee et al. (1988) identified reference value, comparison ease, and need urgency as determinants of price sensitivity. Zeithaml (1988) conceptualized purchase intention as a customer's readiness to transact, shaped by perceived value and perceived risk. Varian (2014) supplied the microeconomic underpinnings for analyzing pricing and consumer choice, particularly the role of information asymmetry in purchase decisions. In the 3D printing setting, factors such as student deadline pressure and the degree of customization can exert substantial influence on purchase intention. The relationship between customization and purchase intention, in particular, has not been empirically examined in the context of 3D printing services. The present study addresses this gap by quantifying the deal rate differential between customized and standard orders, thereby linking Zeithaml's (1988) theoretical construct with operational data.

Content Marketing and Content Strategy

Pulizzi (2014) described content marketing as the creation and distribution of relevant, valuable content to attract and retain a clearly defined audience. Holliman and Rowley (2014) argued that effective B2B content must address customer information requirements at every phase of the decision journey, from awareness through post purchase evaluation. Li et al. (2024) studied customization within 3D printing enabled hybrid manufacturing supply chains, demonstrating that customization capabilities reshape both supply chain dynamics and customer expectations. For SME 3D printing firms, a content strategy underpinned by customer data can function as a potent competitive differentiator. However, the existing literature offers limited guidance on how 3D printing SMEs should translate customer acquisition data into specific content themes, formats, and scheduling. This study bridges that gap by deriving content recommendations directly from transaction level analysis.

Consumer Behavior Theory

Consumer Behavior Theory, as articulated by Howard and Sheth (1969) in their Theory of Buyer Behavior, posits that purchasing decisions are influenced by inputs from the marketing environment, perceptual constructs through which consumers process these stimuli, and learning constructs through which attitudes and intentions are formed. Ajzen (1991) extended this understanding through the Theory of Planned Behavior, which argues that purchase intention is shaped by attitudes toward the behavior, subjective norms, and perceived behavioral control. In the 3D printing context, Consumer Behavior Theory explains why customers who provide detailed customization specifications exhibit higher deal rates. When a customer articulates dimensions, material preferences, or print orientation, they have progressed through the perceptual and learning constructs to form a concrete purchase intention. The urgency of need, such as student thesis deadlines, further accelerates this process by reducing the time available for deliberation, thereby strengthening the relationship between intention and action. This theoretical lens directly informs the custom order effect documented in this study, where orders accompanied by customization descriptions achieved an 80.5% deal rate compared with 49.5% for standard orders.

Customer Value Theory

Customer Value Theory, grounded in the work of Zeithaml (1988) and extended by Holbrook (1994), conceptualizes value as a tradeoff between perceived benefits and perceived costs. Zeithaml's means end model posits that customers evaluate offerings based on their perception of what is received relative to what is given, and that this evaluation shapes purchase intention. In the 3D printing context,



Customer Value Theory illuminates the inverse relationship between order size and deal rate observed in this study. As order value increases, perceived financial risk rises, and the value tradeoff becomes less favorable from the customer's perspective. The finding that large orders exceeding IDR 1 million convert at only 30.2% while small orders below IDR 50,000 convert at 62.4% reflects the operation of this value calculus: customers facing higher financial stakes engage in more extensive evaluation, comparison with alternatives, and deliberation before committing. This theory also explains the material segment fit phenomenon, where premium materials such as Resin and PETG achieve higher deal rates than base materials such as PLA, because customers selecting premium materials have already resolved the value tradeoff in favor of perceived quality over cost.

Price Perception Theory

Price Perception Theory, as formulated by Monroe (1973), argues that buyers form subjective perceptions of price based on internal reference prices, perceived sacrifice, and the perceived quality signal embedded in the price. Monroe's framework establishes that price is not merely an objective financial figure but a psychological construct that influences both purchase intention and perceived product quality. In the 3D printing context, Price Perception Theory provides a lens for understanding why the deal rate declines systematically as order size increases. Customers evaluating large orders face greater perceived sacrifice and have more opportunities for price comparison with alternative manufacturing methods such as CNC machining or injection molding. The finding that print duration dominates the pricing structure, at 64 to 72% of total price, adds a dimension specific to additive manufacturing that has not been explored in the price perception literature: when the primary cost driver is machine time rather than material, customers may struggle to form accurate reference prices, leading to increased deliberation and lower conversion rates. This theory directly informs Pillar 2 (Price Education) of the proposed content strategy, which addresses price perception gaps through transparent cost breakdowns and estimation tools.

Relationship Marketing Theory

Relationship Marketing Theory, grounded in the commitment trust framework of Morgan and Hunt (1994), posits that successful long term relationships between firms and customers are built on commitment and trust, and that these relationships generate superior economic outcomes through reduced transaction costs, increased customer loyalty, and positive word of mouth. Grönroos (1997) extended this perspective by arguing that value is not created at the point of sale alone but throughout the entire customer relationship, and that firms should shift from a transaction focus to a relationship focus. Reichheld & Schefter (2000) applied this theory to the digital environment, demonstrating that E loyalty serves as a primary driver of sustainable profitability. In the 3D printing context, Relationship Marketing Theory explains the finding that repeat customers generate 71.2% of total revenue and that the top 20% of customers account for 75% of all revenue. The Pareto like distribution of customer profitability, documented in this study, aligns with the relationship marketing principle that retaining existing customers yields disproportionately higher returns than acquiring new ones. This theory directly informs Pillar 4 (Retention and Upsell) of the proposed content strategy, which prioritizes WhatsApp broadcast communications and loyalty content for repeat customers.

Synthesis of Theoretical Perspectives

The four theoretical perspectives converge to provide a comprehensive foundation for the proposed five stage framework, as illustrated in Figure 1. Consumer Behavior Theory explains how customers form purchase intentions through perceptual and learning constructs, with customization behavior serving as an observable signal of advanced intention that can be captured at the data analysis stage. Customer Value Theory explains the tradeoff between perceived benefits and costs that governs deal rates across different order sizes and material types, directly informing the customer value analysis stage. Price Perception Theory explains how subjective price evaluations, reference price formation, and perceived sacrifice influence conversion at different price tiers, informing both the value analysis and strategy selection stages. Relationship Marketing Theory explains why customer retention drives the majority of revenue and why relationship building should be prioritized over broad acquisition in the execution stage. The synthesis reveals that these theories operate at complementary levels of the customer

journey: Consumer Behavior Theory and Price Perception Theory primarily inform the early stages by explaining how customers form intentions and evaluate offerings, Customer Value Theory bridges the middle stages by connecting customer evaluation to the value proposition embedded in pricing and material selection, and Relationship Marketing Theory informs the later stages by emphasizing the importance of retention and relationship building in marketing execution. Together, these theories provide a multi level explanation of customer behavior in the 3D printing industry, from initial intention formation through transaction completion to long term relationship maintenance.

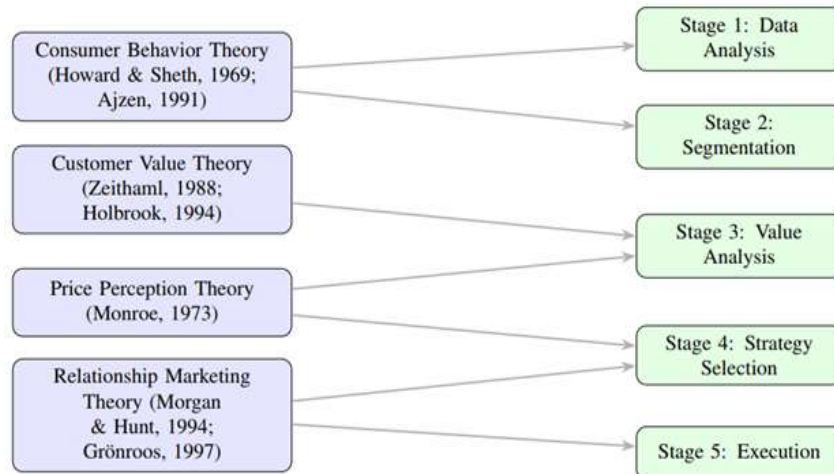


Figure 1. Synthesis of Theoretical Perspectives and Framework Stages

Proposed Conceptual Framework

Synthesizing the reviewed literature, this study puts forward a five stages framework: (1) Customer Acquisition Data Analysis; (2) Customer Segmentation; (3) Customer Value Analysis; (4) Marketing Strategy Selection; and (5) Digital Marketing Execution including content strategy. Figure 1 depicts the conceptual model.

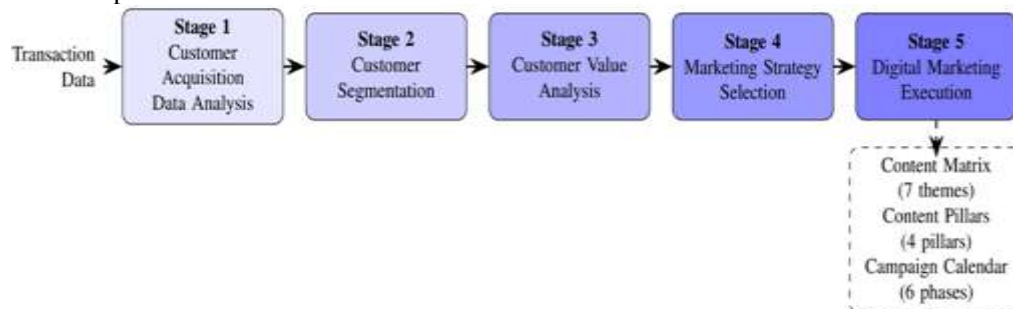


Figure 2. Proposed Conceptual Framework: Five Stage Data Driven Digital Marketing Model

Source: Developed by the author(s), 2025

This framework departs from earlier models by integrating material dimensions, duration based pricing structures, and content strategy in a manner specifically calibrated for the 3D printing industry. The sequential design ensures that each analytical stage feeds directly into the next, culminating in a content strategy that is traceable to specific empirical observations rather than generic best practices.

III. RESEARCH METHOD

Research Type and Approach

This study employs a mixed method research design with a single holistic case study strategy (Yin, 2018). The case study approach was selected because the study examines a contemporary phenomenon, namely data driven marketing in the 3D printing industry, within its real operational

context where the boundaries between the phenomenon and its context are not clearly evident. A single case design was deemed appropriate because the objective is not to generalize findings to a population but to develop and test a framework within a specific operational setting, providing analytical generalization rather than statistical generalization.

The mixed method approach combines quantitative and qualitative components. The quantitative component involves descriptive statistical analysis of 1,484 transaction records, including frequency counts, percentages, medians, means, cross tabulations, and Pareto analysis. The qualitative component encompasses interpretive analysis of customer behavior patterns, material preferences, and strategic implications derived from the quantitative findings. This combination was chosen because quantitative analysis alone can identify patterns in the data but cannot explain why those patterns occur, while qualitative interpretation provides the strategic reasoning behind the observed patterns. The integration of both approaches enables a more complete understanding of customer acquisition behavior in the 3D printing context.

Purposive sampling was used to select the case study site. Tridiku Teknokarya Indonesia was selected based on three criteria: (1) the company maintains complete transaction records for each order, including material specifications, pricing components, and deal outcomes; (2) the company serves all three customer segments relevant to this study, namely Students, General customers, and Companies; and (3) the study period of July to December 2025 encompasses one full academic semester cycle, capturing both peak demand periods and holiday troughs, which is essential for analyzing seasonal patterns.

Research Context

The case was conducted at Tridiku Teknokarya Indonesia, a medium scale 3D printing firm headquartered in Surabaya, Indonesia. The company serves three distinct customer segments: Students, who primarily request architectural models and academic prototypes; General customers, who order functional parts, hobby items, and miniatures; and Companies, who require technical components and functional parts for industrial applications. The firm operates both Fused Deposition Modeling and resin printing systems capable of processing PLA, PETG, ABS, TPU, and Resin materials. At the time of data collection, the company maintained an active customer database and recorded transaction details for each order, including material specifications, pricing components, and deal outcomes.

Population and Sample

The population of interest comprises all transaction records generated by Tridiku Teknokarya Indonesia during the study period. A census sampling approach was adopted, meaning all available transaction records within the defined timeframe were included in the analysis. The sampling frame covers the period from July through December 2025, yielding a total of 1,484 orders from 401 unique customers. No exclusion criteria were applied beyond the temporal boundary, ensuring that the dataset represents the complete operational activity of the firm during the study period. This census approach eliminates sampling bias and provides a comprehensive basis for segment level comparison.

Data Sources

Data were extracted from the company's transaction logs, which serve as a secondary data source. The logs contain structured fields for each order, including:

1. *Customer data*: unique identifier, segment category (Student, General, Company), order frequency, deal status (Deal or No Deal), acquisition source (Google, Instagram, Referral, or unrecorded).
2. *Product and material data*: material type (PLA, Resin, ABS, PETG, TPU), product category (Architectural Model, Prototype, Miniature, Part), print weight in grams, print duration in hours.
3. *Pricing data*: material charge in Rupiah, duration charge in Rupiah, finishing charge in Rupiah, discount amount, total order value.
4. *Temporal data*: order date, month, week number, lead time from inquiry to completion.
5. *Order description*: presence or absence of customization specifications provided by the customer.

The total recorded revenue across all 1,484 orders amounts to IDR 442,556,095. Data extraction was performed by exporting the transaction log from the company's order management system into a structured spreadsheet format for subsequent analysis.

Operational Definitions of Key Concepts

Table 1 defines the key concepts used in this study, along with their operational definitions, indicators, and measurement scales.

Data Collection Technique

Data collection was performed through a structured export of the company's transaction records for the period July to December 2025. The export process involved the following steps. First, the complete transaction log was retrieved from the company's order management system. Second, each record was verified for completeness, ensuring that key fields such as customer identifier, material type, total price, and deal status were populated. Third, records with missing critical fields were flagged and excluded from segment level analysis where the missing field was relevant, though they were retained for aggregate level calculations. Fourth, the cleaned dataset was organized into a spreadsheet with each row representing a single order and each column representing a variable. No personally identifiable customer information was retained beyond an anonymized unique identifier to protect customer privacy.

Table 1. Operational Definitions of Key Concepts

Concept	Operational Definition	Indicators	Measurement
Customer Acquisition Funnel	Sequential process of customer conversion from initial inquiry to loyal status	Orders received, unique customers, closing rate, repeat rate, loyal rate	Count and percentage
Deal Rate	Proportion of customer inquiries that result in a completed transaction	Number of deals divided by total inquiries	Percentage
Customer Segment	Categorization of customers based on primary need type and organizational context	Student, General, Company	Categorical
Average Order Value (AOV)	Mean monetary value of orders within a given segment	Total revenue divided by number of orders	Rupiah
Custom Order	Order accompanied by detailed customization description from the customer	Presence or absence of written specifications	Binary (Yes/No)
Material Segment Fit	Degree of alignment between material type and customer segment	Deal rate for each material segment combination	Percentage
Revenue Concentration	Distribution of total revenue across order size categories	Revenue share by price range tier	Percentage
Price Composition	Breakdown of total price into material, duration, and finishing components	Material, duration, finishing cost as percentage of total	Percentage
Content Pillar	Data driven thematic category for marketing content	Portfolio, Price Education, Urgency, Retention and Upsell	Categorical

Source: Developed by the author(s), 2025

Data Analysis Technique

The analytical procedures applied to the dataset included the following techniques. Descriptive statistics were computed for each segment, including order counts, percentages, medians, means, and standard deviations for key variables such as order value, print weight, and deal rate. Cross tabulation was performed to examine the relationship between segments and material types, product categories, and price ranges. Funnel analysis was conducted to trace the progression of customers from initial inquiry through deal, repeat, and loyal stages. Pareto analysis was applied to the revenue distribution across price tiers to identify concentration patterns. Seasonal decomposition was performed at the monthly and weekly levels to identify temporal patterns in order volume. Comparative analysis across segments was used to identify statistically meaningful differences in deal rates, revenue contribution, and behavioral patterns. All analyses were conducted using standard spreadsheet software, ensuring that the methods

are replicable by SME practitioners without specialized statistical software.

IV. RESULTS AND DISCUSSION

Description of Research Object

Tridiku Teknokarya Indonesia operates as a medium scale 3D printing service provider based in Surabaya. During the six months study period from July to December 2025, the company processed 1,484 orders from 401 unique customers, generating total recorded revenue of IDR 442,556,095. The company maintains a diverse material portfolio, including PLA, Resin, ABS, PETG, and TPU, and serves three primary customer segments: Students (academic purposes), General (individual hobby and functional use), and Companies (industrial and technical applications). The firm's transaction records provide a comprehensive view of customer behavior, material preferences, pricing structures, and conversion outcomes across a full operational cycle that includes both academic calendar peaks and holiday troughs. This dataset offers a suitable basis for testing the proposed five stage framework because it captures the full heterogeneity of a real 3D printing operation, from small student orders to large industrial contracts.

Customer Data Analysis and Segmentation Customer Acquisition Funnel

Table 2. Customer Acquisition Funnel (July to December 2025)

Stage	Count	% Unique Customers
Orders Received	1,484	not applicable
Unique Customers	401	100%
Ever Closing	239	59.6%
Repeat (2 or more orders)	203	50.6%
Loyal (4 or more orders)	102	25.4%

Source: Processed by the author(s), 2025

Among the 401 customers, only 59.6% progressed to completing at least one transaction. Yet of those who closed, 85% returned for repeat orders, and 50.2% of repeat customers eventually attained loyal status with four or more orders. Repeat customers generated 71.2% of total revenue, corroborating the principle articulated by Reichheld and Schefter (2000) that customer retention serves as the principal driver of revenue. The distribution of order frequency follows a Pareto like pattern: 48 customers, representing 12% of the base with seven or more orders, produced 30.2% of revenue. The top 20% of customers accounted for 75% of total revenue. This concentration pattern has immediate implications for resource allocation, suggesting that retention focused marketing directed at the top quintile of customers yields disproportionate returns compared with broad acquisition spending.

Seasonal Patterns and Peak Week

Table 3 details the monthly order distribution across segments, while Figure 3 presents a line chart that traces the seasonal trajectory of each segment across the six months period.

Table 3. Monthly Order Distribution by Segment

Month	Student	Company	General	Total
July	61	20	54	135
August	0	13	93	106
September	16	82	205	303
October	63	33	225	321
November	190	32	192	414
December	58	23	124	205

Source: Processed by the author(s), 2025

The student segment displays dramatic seasonality. There were zero orders during August, which coincides with the semester holiday, followed by a November surge reaching 190 orders. More granular weekly analysis reveals that Week 46 (November 10 to 15) alone produced 192 orders, almost exclusively from students confronting thesis submission and defense deadlines. This level of temporal granularity is essential for campaign planning, as it identifies not merely peak months but specific weeks

during which demand spikes extraordinarily. Monthly deal rates fluctuated considerably, spanning from 35.6% in September as the lowest to 64.4% in July as the highest. September presents an intriguing case. Despite high order volume of 303, it registered the poorest deal rate because a large proportion of Company segment inquiries during this period culminated in no transaction. This finding suggests that high inquiry volume does not necessarily translate to high conversion, and that the composition of inquiries by segment matters more than total volume for predicting deal rates.

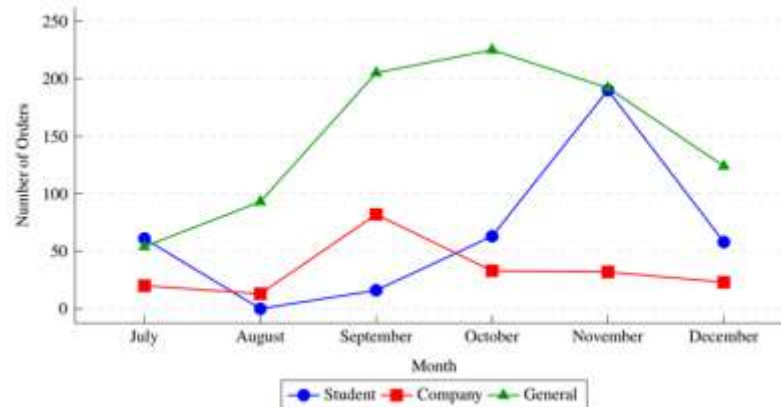


Figure 3. Monthly Order Distribution by Segment (Line Chart)

Source: Processed by the author(s), 2025

Customer Segmentation

Table 4 summarizes the profiles of the three principal segments, and Figure 3 uses a horizontal bar chart to compare deal rate against order share for each segment, visually demonstrating that conversion performance and volume contribution do not align.

Table 4. Customer Segment Profile

Dimension	Student	General	Company
Order Count	388 (26.1%)	893 (60.2%)	203 (13.7%)
Primary Material	PLA (91%)	PLA (62%), Resin (19%)	ABS (43%), PLA (38%)
Primary Product	Arch. Model (68%)	Part (69%)	Part (82%)
Median Order Value	IDR 118,484	IDR 60,134	IDR 89,000
Mean AOV	IDR 430,027	IDR 245,275	IDR 291,428
Deal Rate	64.7%	49.9%	46.8%
Median Weight	70 g	21 g	26 g
Total Revenue	IDR 166,420,357	IDR 217,558,720	IDR 58,577,018

Source: Processed by the author(s), 2025

The student segment exhibits strong homogeneity in material preference, with PLA at 91%, and product type, with architectural models at 68%. It also shows the highest median print weight of 70 g, which reflects large format architectural models. Its leading deal rate of 64.7% is indicative of pressing deadline driven demand. The General segment displays the greatest diversity in both materials and products, alongside the lowest median AOV of IDR 60,134, suggesting predominantly small to medium orders. The Company segment is characterized by ABS dominance at 43% and functional parts at 82%, with the lowest deal rate of 46.8% attributable to extended procurement cycles and the availability of competing manufacturing alternatives.

Figure 4 makes a critical insight immediately visible. The segment with the highest deal rate, Student at 64.7%, contributes the smallest share of total orders at 26.1%. Meanwhile, the segment commanding the largest order volume, General at 60.2%, achieves only a middling deal rate of 49.9%. This divergence between conversion performance and volume contribution challenges the assumption that high volume segments are inherently the most valuable. It carries direct implications for marketing resource allocation, suggesting that budget decisions should be guided by per segment profitability

rather than raw volume.

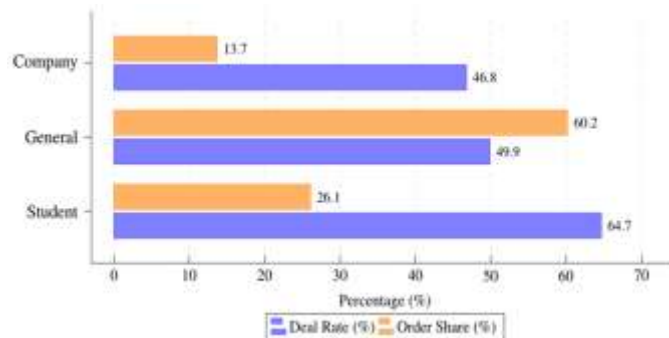


Figure 4. Deal Rate vs. Order Share by Segment: Volume Does Not Equal Conversion

Source: Processed by the author(s), 2025

Customer Value and Behavioral Insights

Revenue Contribution and Revenue Concentration Paradox

Although the General segment accounts for the largest share of orders at 60.2%, its revenue per order is the lowest at IDR 243,619. The student segment, with only 26.1% of orders, generates the highest revenue per order at IDR 428,918. The Company segment, despite having the fewest customers at 22, achieves the highest revenue per customer at IDR 2,662,592, driven by a high order frequency of 9.23 orders per customer.

Analysis of price distribution reveals a stark revenue concentration paradox. A mere 4.9% of orders valued above IDR 1 million contribute 52.7% of total revenue, whereas 42.6% of orders below IDR 50,000 account for only 2.4%. The two highest price tiers, orders exceeding IDR 1 million and orders between IDR 500,000 and IDR 1 million, together account for 72.4% of revenue while representing only 13.7% of total orders. This concentration underscores the disproportionate value of high value orders and the strategic necessity of dedicated nurturing for these transactions. The finding aligns with Cooper and Kaplan's (1988) observation that customer profitability is unevenly distributed, but extends it by showing that the concentration operates not only at the customer level but also at the order level within a single firm.

Material Preferences and Material Segment Fit

Table 5 presents the segment × material matrix, and Figure 4 ranks all segment material combinations by deal rate, making the material segment fit visually apparent.

Table 5. Segment × Material Matrix: Orders, Revenue, and Deal Rate

Segment	Material	Orders	Revenue (IDR)	Deal Rate	Note
Student	PLA	355	123,728,187	64.5%	Dominant, arch. models
Student	Resin	9	491,315	100%	All deals, precision
Student	PETG	11	2,859,969	81.8%	Engineering parts
General	PLA	557	161,267,745	46.0%	Largest volume
General	Resin	168	23,220,682	58.9%	Miniatures, premium
General	ABS	58	17,722,680	58.6%	Industrial parts
Company	ABS	86	10,798,404	50.0%	Standard industrial
Company	PLA	78	42,873,754	32.1%	Prototypes, cancellations
Company	PETG	10	886,571	80.0%	Highest B2B conversion

Source: Processed by the author(s), 2025

Several patterns emerge from the analysis. The student × Resin combination achieves a perfect 100% deal rate, meaning every Resin order placed by a student converted into a transaction. The Company × PETG pairing attains an 80% deal rate, substantially exceeding the Company × PLA rate of 32.1%. These results point to an optimal material segment alignment: Resin for Students and PETG

for Companies yield exceptionally high conversion, presenting clear cross selling opportunities. Four lowest ranked combinations all involve PLA or ABS orders from the General and Company segments, while the top three positions are occupied by premium material orders, specifically Resin and PETG, placed by high intent segments. This finding suggests that material selection is not merely a technical decision but also serves as a behavioral signal of purchase commitment

Price Composition per Segment

Table 6 decomposes the pricing structure for each segment.

Table 6. Price Composition per Segment

Segment Avg	Material (IDR)	Avg Duration (IDR)	Avg Finishing (IDR)	% Mat	% Dur	% Fin	Avg Total (IDR)
Student	134,389	358,415	2,639	27.1%	72.3%	0.5%	430,027
General	70,733	137,082	6,148	33.1%	64.1%	2.9%	245,275
Company	75,174	195,686	7,143	27.0%	70.4%	2.6%	291,428

Source: Processed by the author(s), 2025

Across all segments, print duration costs constitute the dominant portion of pricing, ranging from 64% to 72%. This finding carries a significant managerial implication. Machine time represents the most precious resource in 3D printing operations, and maximizing machine throughput is more critical to profitability than negotiating material costs downward. This insight also has implications for pricing strategy: firms that price primarily on material weight may be systematically undercharging for long duration prints, particularly in the Student segment where duration accounts for 72.3% of total price.

Price Sensitivity

Table 7. Price Sensitivity: Deal Rate vs. Order Size

Price Range	Orders	Deal Rate	Revenue (IDR)	% Orders	% Revenue	Median (IDR)
Below IDR 50,000	121	62.4%	10,643,169	42.6%	2.4%	18,392
IDR 50K to 100K	62	58.8%	18,141,536	21.8%	4.1%	70,084
IDR 100K to 250K	47	57.8%	43,380,197	16.5%	9.8%	147,400
IDR 250K to 500K	15	49.3%	49,885,798	5.3%	11.3%	347,417
IDR 500K to 1 million	25	46.8%	87,174,260	8.8%	19.7%	677,467
Above IDR 1 million	14	30.2%	233,331,135	4.9%	52.7%	1,713,534

Source: Processed by the author(s), 2025

A clear inverse relationship emerges between order size and deal rate. The smallest orders, those below IDR 50,000, convert at 62.4%, while the largest orders, those exceeding IDR 1 million, convert at only 30.2%. However, these large orders represent just 4.9% of the total yet generate 52.7% of all revenue. This dual pattern creates a strategic tension. High value orders demand more intensive sales effort and nurturing yet deliver disproportionate revenue impact. Low value orders convert readily but contribute marginally to the bottom line. The implication for marketing strategy is that different price tiers require fundamentally different approaches: low value orders can be served through self service and automated quotation tools, while high value orders necessitate personalized follow up, detailed proposals, and relationship management.

Custom Order Effect on Deal Rate

A supplementary analysis surfaced a finding of considerable theoretical importance. Orders that include customization descriptions, where customers provide detailed specifications, notes, or design requirements, exhibit a markedly higher deal rate than those submitted without such descriptions. Table 8 summarizes the comparison, and Figure 5 visualizes the deal versus no deal proportions for each order type.

Table 8. Impact of Custom Orders on Deal Rate

Order Type	Count	% of Total	Deal Rate	Median (IDR)
With Custom Description	185	12.5%	80.5%	85,000
Without Description	1,299	87.5%	49.5%	70,734

Source: Processed by the author(s), 2025

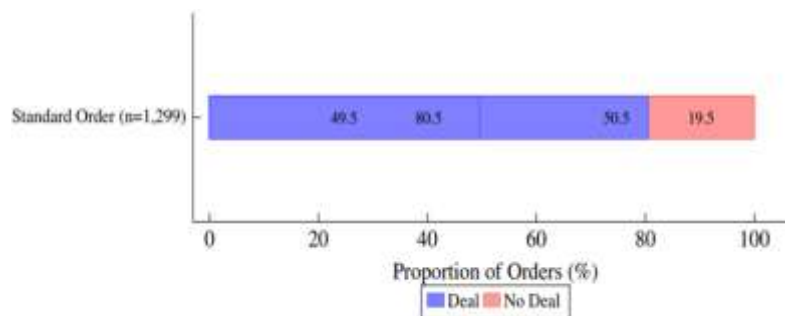


Figure 5. Custom Order Effect: Deal vs. No Deal Proportion by Order Type

Source: Processed by the author(s), 2025

The 31 percentages point chasm between custom orders at 80.5% and standard orders at 49.5% represents a finding that bridges Zeithaml's (1988) purchase intention framework with 3D printing practice. Customers who invest the effort to articulate detailed specifications, such as dimensions, color preferences, infill density, or print orientation, have already advanced to the consideration to purchase phase of the decision journey. They are not casual browsers but individuals with concrete, well defined needs. The practical prescription is straightforward. Firms should actively encourage prospective customers to supply as much specification detail as possible at the quotation stage, for instance by deploying a structured quotation form with prompts that elicit granular design requirements. Figure 4 makes the magnitude of this effect unmistakable. The blue, or Deal, portion dominates the Custom Order bar at 80.5%, while the Standard Order bar is split almost evenly between Deal and No Deal. This visual evidence supports the argument that customization behavior functions as a reliable proxy for purchase intention in the 3D printing context, a connection not previously documented in the literature.

Deal Rate by Product Category

Table 9 reports deal rates across product categories.

Table 9. Deal Rate by Product Category

Category	Order Count	Deal Rate	Revenue (IDR)	Median AOV (IDR)
Architectural Model	28	68.5%	88,098,804	107,867
Prototype	28	59.4%	64,621,874	111,917
Miniature	26	51.2%	50,602,378	85,284
Part	201	48.0%	200,582,975	60,309

Source: Processed by the author(s), 2025

The pattern is consistent. Architectural models command the highest deal rate at 68.5% because the underlying need is both highly specific and time pressurized, typically driven by assignment deadlines. Parts register the lowest deal rate at 48.0% due to the availability of substitute manufacturing processes such as CNC machining and injection molding. The principle that emerges is that greater specificity and urgency of need correspond to higher conversion. This finding resonates with purchase intention theory, which posits that clear specifications diminish perceived risk and accelerate the purchase decision (Zeithaml, 1988a). It also reinforces the custom order effect documented in the preceding section: both product specificity and customization behavior point to the same underlying mechanism, namely that customers who arrive with well defined requirements convert at substantially higher rates.

Digital Marketing Strategy and Execution Marketing Strategy Selection per Segment

Drawing upon the customer value analysis, segment specific strategies were formulated by linking behavioral patterns with established marketing theory. Table 10 encapsulates the decision matrix.

Table 10. Decision Matrix: Segment → Marketing Strategy

Dimension	Student	General	Company
Need Profile	Arch. models, tight deadlines	Functional parts, hobby, varied	Technical parts, repeat orders, precision specs
Dominant Material	PLA IDR 350/g	PLA + Resin	ABS IDR 1,000/g
Deal Rate	64.7%	49.9%	46.8%
Primary Channel	Instagram, TikTok	Google Search, Instagram	Google, LinkedIn, Referral
Key Message	“Ready before your deadline”	“Print anything, fast”	“Trusted production partner”
Timing	October to November peak	September to November stable	August to September project start
Priority	Volume and retention	Upsell and LTV	Nurturing and follow up

Source: Developed by the author(s), 2025

Data Driven Upselling Strategy

Beyond segment level strategies, the analysis of price sensitivity and material preferences informed a structured upselling approach. Table 11 maps transitions from the base material, PLA, to premium alternatives.

Table 11. Upsell Strategy: PLA → Premium Material

Transition	Price/g from	Price/g to	Multiplier	Use Case	Target Segment	Upsell Message
PLA → Resin	IDR 350	IDR 5,000	14x	High detail miniatures	General, Company	“5x finer detail with Resin”
PLA → ABS	IDR 350	IDR 1,000	2.9x	Heat resistant parts	Company	“ABS withstands 100°C”
PLA → PETG	IDR 350	IDR 600	1.7x	Impact resistant parts	General, Company	“PETG: impact resistant and light”

The data underpinning this strategy is compelling. The Company × PETG pairing achieves an 80% deal rate, and the Student × Resin combination reaches 100%. Customers who transition to premium materials tend to be highly committed, suggesting that upselling not only raises revenue per order but also improves deal rate, as the selection of premium materials typically follows a more thorough evaluation process.

Digital Channel Strategy

Table 12 outlines the digital marketing channel allocation per segment.

Table 12. Digital Marketing Channel Strategy per Segment

Segment	Primary Channel	Secondary Channel	Content Format	Timing
Student	Instagram, TikTok	WhatsApp (closing)	Before and after, timelapse, price estimates	Monday to Wednesday, September to November
General	Google Search (SEO), Instagram	WhatsApp, Marketplace	Price FAQ, material demos, calculator	Monday to Wednesday, year round
Company	Google, Referral	LinkedIn, WhatsApp	B2B landing page, datasheets, formal quotes	Thursday to Friday, August to September

Validation through acquisition source data reveals a notable pattern. Google achieves a 92.3% deal rate from 6 unique customers, Referral 76.9% from 4 customers, and Instagram 30.4% from 18 customers. Although Instagram delivers the highest number of unique customers, its conversion is comparatively low. Google, by contrast, attracts fewer customers but converts them at an exceptional rate. This pattern is consistent with search intent marketing theory (Chaffey & Ellis-Chadwick, 2019), which posits that customers arriving through active search queries possess higher purchase readiness than those reached through social media exposure.

Content Matrix: Seven Data Driven Themes

The study proposes a content matrix organized around seven themes, each mapped to the three segments with tailored formats and posting frequencies. Table 13 presents the full matrix.

Table 13. Content Matrix: Theme × Segment × Format

Theme	Student	General	Company	Format	Freq.
Portfolio	Arch. models, scale 1:200 to 500, PLA	Hobby parts, miniatures, accessories	Industrial components, brackets, jigs ABS	Photo, Carousel	3x/wk
Material Education	PLA: lightweight, many colors	PLA vs Resin: when to use which	ABS vs PLA: heat resistance	Infographic, Reels	2x/wk
Price Transparency	“50cm model cost?” breakdown	Calculator: weight × material × duration	Formal price list: ABS/PETG + volume discount	Story, Landing	2x/wk
Process and Behind the Scenes	10hr model timelapse to 1 min	From STL to product: 3 steps	QC process, tolerances, datasheets	Reels, Video	1x/wk
Urgency	“Defense in 3 days? We can.”	“Order now, done in X days”	Lead time guarantee for contracts	Story, CTA	September to November
Custom Design	Campus logos, mascots, mini helmets	Custom from photo or sketch, STL mods	DFM consultation, technical design	Before and after	1x/wk
Social Proof	Testimonials: passed defense, model on table	Repeat customer reviews, unboxing	Industry case studies (anonymous), referrals	Quote, Screenshot	2x/wk

Each theme in the matrix is anchored in the analyzed data. The Portfolio theme assumes prominence because custom orders with detailed descriptions achieve an 80.5% deal rate, indicating that exposure to concrete examples strengthens conversion. The Material Education theme steers customers toward materials aligned with their requirements, reinforcing the upsell strategy. The Price Transparency theme directly counters the deal rate decline observed on larger orders, which drops from 62% to 30%, by furnishing transparent cost breakdowns. The Urgency theme is deployed principally for the student segment, capitalizing on the extreme November demand peak. The Custom and Design theme motivates customers to articulate detailed specifications; a behavior empirically linked to higher deal rates. The Social Proof theme bolsters credibility, particularly for the Company segment where the deal rate is lowest.

Four Data Driven Content Pillars

Distilled from the seven themes, four primary content pillars were formulated, each tethered to specific data evidence. Table 14 details the pillars.

Table 14. Four Data Driven Content Pillars

Pillar	Supporting Data	Key Content Ideas	Freq.	CTA
P1: Portfolio	Custom order deal rate 80.5% vs 49.5% (+31 pts)	Photos of models, hobby parts, industrial components per segment	3x/wk	“Want this? Chat now” → WhatsApp
P2: Price Education	Deal rate drops 62% to 30% on orders above	Breakdown: 68% duration + 30% material. Estimation	2x/wk	“Check price estimate” →

	1M; 68% price equals duration	calculator		form
P3: Urgency	Week 46: 192 orders per week, all Students	“How many days to deadline?” Countdown. Lead time guarantee	Intensive September to November	“Contact now, free estimate”
P4: Retention and upsell	48 customers (12%) equal 30% revenue. Top 20% equal 75% revenue	“Ordered PLA? Try Resin.” Loyalty content via WhatsApp	1x/wk via WhatsApp	Special offers for repeat customers

Each pillar responds to a specific data driven insight. Pillar 1, Portfolio, exploits the custom order effect by displaying concrete results that encourage prospective customers to articulate detailed specifications, which has been demonstrated to elevate deal rates. Pillar 2, Price Education, counteracts price sensitivity on large orders through structural cost transparency. Pillar 3, Urgency, leverages the extreme seasonality of the Student segment, which saw a peak week of 192 orders. Pillar 4, Retention and Upsell, capitalizes on the Pareto distribution. Since the top 20% of customers generate 75% of revenue, retention and upsell communications delivered via WhatsApp broadcast constitute a strategic priority.

Campaign Calendar Based on Data Patterns

The study translates the seasonal patterns observed in 2025 into a structured campaign calendar for subsequent operational cycles. Table 15 outlines the six phases schedule.

Table 15. Campaign Calendar Based on 2025 Data Patterns

Period	Phase	Segment Focus	Campaign Action	Target KPI	Ref. 2025
January to February	Warm up	General, Company	Portfolio update, awareness, WhatsApp repeat activation	Inquiries, source tracked	241
March to April	Semester Start	Student, General	Model price education, SEO “3D print model”	Organic traffic	303
May to June	Defense and Thesis	Student (peak)	Urgency “defense deadline”, model timelapse	Deal rate above 60%	414
July to August	Holiday and Low	General, Company	B2B outreach, content batching, Resin upsell	Company pipeline	241
September to October	Inquiry Surge	All segments	Activate all channels. Improve follow up speed	Deal rate 35% to 50% plus	624
November to December	Peak Season	Student (dominant)	Full blast: daily urgency, WhatsApp auto response	414 plus orders per month	619

The calendar illustrates the conversion of historical patterns into actionable plans. The Warm up phase in January and February concentrates on reactivating repeat customers responsible for 75% of revenue. The Semester Start phase in March and April initiates awareness building among Students ahead of the peak. The Defense and Thesis phase in May and June constitutes the urgency phase, targeting a deal rate exceeding 60%. The Holiday phase in July and August redirects attention to B2B while Students are inactive. The Inquiry Surge phase in September and October confronts the challenge of depressed deal rates, which stood at 35.6% in September, through accelerated follow up. The Peak Season phase in November and December represents full capacity execution, requiring advance machine preparation for the student order surge.

Framework Validation

Validation was performed by juxtaposing pre framework and post framework marketing approaches. Table 16 documents this comparison.

Table 16. Comparison of Strategies Before and After Framework

Aspect	Before Framework	After Framework
Targeting	Undefined (broadcast)	Specific segments with distinct profiles
Channels	Facebook and Instagram undifferentiated	Instagram (Student), Google (General), LinkedIn (Company)
Content	Generic content	7 theme content matrix, 4 data driven pillars
Pricing	Uniform pricing	Tiered pricing based on segment and order size
Timing	Posting without schedule	6 phase calendar based on seasonal patterns
Upsell	None	PLA to Resin, PLA to ABS, PLA to PETG
Measurement	No metrics	Deal rate, CAC, repeat rate, revenue per customer
Quotation	Free form	Structured form to encourage custom orders (80.5% deal rate)

Discussion

Theoretical Contributions

This study advances the literature in several directions. First, the proposed framework integrates material dimensions, duration-based pricing, and content strategy within customer acquisition analysis. This synthesis has not been encountered in existing SME digital marketing scholarship (Kumar et al., 2026; Supriyadi & Edi Pranyoto, 2025). The finding that print duration dominates the pricing structure, at 64 to 72%, enriches pricing theory in additive manufacturing, extending the work of Jain et al. (2024) and Bi and Wu (2025) by providing empirical evidence that duration-based pricing is not merely a theoretical model but an operational reality with strategic implications.

Second, the study documents the custom order effect. Orders accompanied by customization descriptions achieve an 80.5% deal rate compared with 49.5% for standard orders. This discovery connects Zeithaml's (1988) purchase intention construct with 3D printing practice, demonstrating that customers who articulate specifications have already progressed to the consideration to purchase stage. The practical corollary is that structured quotation forms can materially elevate conversion rates, a finding with implications extending beyond 3D printing to any service business where customer specifications can be solicited at the inquiry stage.

Third, the research corroborates the revenue concentration paradox within the 3D printing industry. The Pareto like distribution, where 20% of customers generate 75% of revenue and 4.9% of orders produce 52.7% of revenue, aligns with Cooper and Kaplan's (1988) observation that customer profitability is unevenly distributed. A further nuance emerges. The highest volume segment, General at 60.2% of orders, does not coincide with the highest per customer profitability. This contests the prevalent assumption that volume equates to profitability and suggests that marketing resource allocation models based solely on volume metrics may be systematically misdirected.

Fourth, the study establishes that material segment fit influences deal rate. The student × Resin combination at 100% and the Company × PETG combination at 80% demonstrates that material selection functions not solely as a technical preference but also as a signal of purchase intention. This deepens understanding of the relationship between product attributes and purchase intent, suggesting that in customized manufacturing contexts, the choice of premium materials may serve as a behavioral marker of customer commitment.

Fifth, the research operationalizes customer acquisition data into a concrete content strategy comprising seven themes, four pillars, and a six phases calendar. This forges a link between analytical insight and marketing execution that has been largely absent from both 3D printing research (Holzmann et al., 2020) and content marketing scholarship (Holliman & Rowley, 2014; Pulizzi, 2014). By tracing each content recommendation to a specific empirical observation, the study provides a template for how data driven content strategy can be constructed in practice.

Managerial Implications

For practitioners in 3D printing SMEs, the study yields several actionable recommendations grounded in data. First, routine transaction records constitute an underutilized reservoir of marketing

intelligence. Straightforward analysis of deal rates by segment, material, and order size can surface patterns that remain invisible to intuitive observation. Second, marketing budget allocation should be guided by per segment profitability rather than volume. Students and Companies produce higher revenue per customer despite lower order counts, suggesting that retention and nurturing investments in these segments may yield better returns than broad acquisition spending on the General segment. Third, the deployment of structured quotation forms that prompt customization can meaningfully raise deal rates, shifting conversion from 49.5% to 80.5%. Fourth, data informed upsell pathways, such as PLA to Resin for detail and PLA to ABS for industrial applications, can simultaneously boost AOV and deal rate. Fifth, a campaign calendar synchronized with seasonal patterns enables more efficient allocation of machine capacity and marketing expenditure, particularly in preparation for the extreme Student demand peak in November.

Limitations and Future Research

Several limitations should be acknowledged. First, reliance on a single case study constrains the generalizability of findings. The patterns observed at Tridiku Teknokarya Indonesia may reflect firm specific or regional factors that do not extend to other 3D printing SMEs. Second, acquisition source data was captured for only 4.2% of orders, limiting the robustness of channel level analysis and preventing systematic attribution modeling. Third, the framework does not yet incorporate predictive analytics or machine learning, which could enable demand forecasting and personalized content recommendations. Fourth, the study period of six months captures only one academic cycle, and multi year analysis could reveal whether seasonal patterns are stable or evolving. Future research could extend validation to multiple firms across different geographic markets, implement CRM systems for systematic acquisition tracking, integrate predictive modeling for demand forecasting, and test the framework in adjacent industries such as CNC machining or laser cutting where similar duration-based pricing and segment heterogeneity may apply.

V. CONCLUSION

This study developed and empirically tested a data driven digital marketing framework based on customer acquisition, structured across five stages and tailored to the 3D printing industry, incorporating content strategy and a data informed campaign calendar. Drawing on the case study at Tridiku Teknokarya Indonesia with 1,484 orders from 401 unique customers over six months, four principal findings emerge. First, the framework demonstrated the capacity to convert routine transaction records into actionable marketing intelligence, producing a precise mapping of the most profitable segments and their corresponding strategic approaches. Second, data driven marketing decisions produce recommendations that diverge from intuition: the highest volume segment is not the most profitable per customer, orders with customization descriptions achieve a deal rate 31 percentage points higher than standard orders, and specific material segment pairings exhibit conversion rates substantially above average. Third, the data driven content strategy, comprising seven themes, four pillars, and a six phases campaign calendar, provides a concrete execution blueprint where each element is traceable to specific empirical evidence. Fourth, the framework is accessible to 3D printing SMEs without demanding sophisticated technological infrastructure. Theoretically, the study extends Consumer Behavior Theory by demonstrating that customization behavior functions as an observable proxy for purchase, extends Customer Value Theory by showing that the value tradeoff is mediated by order size in machine time driven pricing, extends Price Perception Theory by revealing that customers lack stable reference prices when the primary cost driver is intangible, and extends Relationship Marketing Theory by confirming that the Pareto distribution operates at both the customer and order levels. Several limitations should be acknowledged. The study relies on a single transaction dataset from one firm, which may reflect firm specific characteristics, local market conditions, and academic calendar dynamics unique to Yogyakarta, constraining generalizability to other firms or regions. The six months observation period captures one academic cycle but does not allow year over year comparison. Acquisition source data was available for only 4.2% of orders, and the study employs descriptive rather than inferential statistical methods. Future research should validate the framework across multiple firms

in different markets, conduct longitudinal studies spanning multiple academic cycles, integrate CRM systems for complete channel tracking, incorporate predictive analytics and machine learning, test the framework in adjacent industries such as CNC machining and laser cutting, and implement intervention studies measuring marketing outcomes before and after framework adoption. Practically, the framework holds potential as a transformation tool for 3D printing SMEs seeking to shift from intuition based to evidence based marketing, demonstrating that actionable intelligence can be derived from routine transaction records using accessible spreadsheet tools.

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Author Contributions

The first author developed the concept, designed the framework, and performed data analysis. The second author validated the framework, reviewed the literature synthesis, and finalized the manuscript. Both authors contributed to the interpretation of findings and approved the final version of the manuscript.

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