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IS BRAND LOYALTY INFLUENCED BY PRICING STRATEGIES IN THE FAST-FASHION INDUSTRY?

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Abstract:
As the fast-fashion industry is estimated to be worth more than 120 billion in 2024, pricing strategies play a vital role in fostering consumer interest in the sector, where brands such as Zara, H&M, and Shein compete fiercely. The research question this investigation will explore is: Is brand loyalty influenced by pricing strategies in the fast-fashion industry? It seeks to validate the hypothesis that dynamic pricing, including flash sales based on AI and personalized discounts, increases brand loyalty by 25 points relative to fixed pricing, which is assessed through the prism of repurchase intent and net promoter scores. An online survey of 250 consumers aged 18-35 in China and the UK was conducted to gather primary data. In both simulated dynamic and fixed pricing conditions, respondents rated loyalty using a 5-point Likert scale. A binary logistic regression was adopted in this study, where loyalty (1 = loyal, score 4 or higher) was the dependent variable, dynamic pricing exposure was the central independent variable, and demographics, income, and brand familiarity were considered as controls. Model diagnostics were used to indicate goodness-of-fit (Nagelkerke R 2 = 0.28).
The key findings suggest that as it was hypothesized, dynamic pricing can raise the likelihood of loyalty by 24.8 percent (0.223, OR = 1.25, $p < 0.05$), yet the results were more pronounced among price-sensitive low-income clients (OR = 1.32, $p < 0.01$). This also applies to the fast-fashion industry of more than $ 120 billion, which is focused on price to initiate consumer interactions amidst the high competition with other brands, such as Zara, H&M, or Shein. The research contributes to the body of knowledge about the topic of pricing-loyalty association, and poses the question of the ethical strategies towards the turbulent markets.

Keywords: Fast-fashion industry, Brand loyalty, Dynamic pricing, Fixed pricing, Consumer behavior, Repurchase intent, Logistic regression and Behavioral economics.

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1 Introduction

1.1 The Fast-Fashion Industry Landscape

The advent of the fast-fashion market has made it a player in the retailing industry at the international level and it is typified by a fast production cycle, trend set designs, and aggressive pricing strategies which have democratized the low-cost clothing market. In 2024, the sector market size was estimated at 136.19 billion with a positive compound annual growth rate (CAGR) of approximately 11% relative to the previous year considering penetration of e-commerce and shift of consumers towards value purchases that are value oriented (Siakki, 2024). The main players, Zara (Inditex), H&M, Shein, and Temu, have taken advantage of this expansion (Bafna, 2025), whereby they have designed thousands of new clothes every week to hitch the short-lived trend without need to maintain high-profit margins through economies of scale and efficiencies in the supply chain.

1.2 The Essential Role of Pricing Strategies.

The core of this competitive landscape is pricing strategy, as it is not only a transactional device but also a key differentiator in an oversaturated market. High-volume production, low-cost sourcing (Bangladesh and Vietnam), and externalization of environmental and labor costs (costs of textile waste, and exploitation of garment workers) allows fast-fashion brands to achieve rock-bottom prices, which frequently fall below $20 per piece (Wood et al., 2021). It is made possible by AI algorithms and real-time data analytics, which enable personalized discounts, flash sales, and surge adjustments depending on demand, inventory levels, and consumer behavior (Ka, 2025). An example is the use of algorithmic pricing by Shein, who provides extremely low entry points (e.g., dresses at $5), which encourages impulse purchases and viral distribution on social media. Conversely, fixed pricing implies an unchanging price level throughout seasons, which indicates stability but may lose to more flexible competitors (Bafna, 2025). With challengers such as Temu threatening incumbents, pricing has become a complex tool in the war of market share as 2024 reports show price sensitivity can affect up to 70% of purchases in this category.

1.3 The Loyalty Paradox in Fast Fashion

The tension between long-term brand loyalty and short-term sales spikes is one of the most acute paradoxes in the industry. Fast fashion is driven by sales volume and ephemerality, with customers disposing of products after a short time of use, but the industry faces infamously low retention (Wood et al., 2021). Data indicates that the most significant issue faced by brands is customer loyalty, as consumers, tempted by endless promotions, practice polygamous behavior, switching between platforms without strong loyalty to a particular label. Unlike their luxury counterparts, a customer is likely to remain loyal to the newness and cost-effectiveness but change suppliers at any time, such as an offer on a different website (Persson and Olsson, 2024). Online markets exacerbate this destruction, as the comparison shopping is amplified by the algorithms, which reduce entry barriers and increase price competitions.

1.4 Research Question and Hypothesis

The research question is a direct attack on this dilemma that is encountered in this study: Is brand loyalty a factor of price strategies in the fast-fashion industry? The hypothesis under consideration is clear and empirically verifiable: Dynamic pricing plans are able to increase brand loyalty by 25 percent compared to fixed pricing based on the more probable repurchase intention in an expectation logistic regression test on the foundations of primary consumer surveys. This hypothesis predicts a positive effect of dynamic pricing that the personification of the discounted of persons appears to be a personal gain increases the degree of emotional involvement and habit purchase, which overpowers the possible inclinations to view manipulation and the 25 percent cut-off is based on meta-analytic norms to the retail economics and is, therefore, false in a statistical sense.

1.5 Project Objectives

1. In order to comment on the theoretical relationships between the pricing strategy and brand loyalty, one would need to synthesize the behavior economics and relationship marketing paradigm, under which the value perception and erosion of trust would be discussed.
2. To gather primary data through designed surveys of more than 200 fast-fashion customers, the measurement of attitudinal and behavioral measures under simulated pricing conditions to achieve ecological validity.
3. In order to use binary logistic regression to model the results of loyalty, it is necessary to quantify the hypothesis in odds ratios, having the confounding variables such as demographics and market exposure controlled.
4. To prove the hypothesis and justify its outcomes, a trade-off between the short-term benefits (e.g. acquisition boosts) and those of the long-term (e.g. fairness perceptions) should be considered and, therefore, guide strategic recommendations of the brands..

1.6 Justification for P302 Pathway

The requirements of an Extended Project Qualification (EPQ) P302 pathway, an investigation or field study, can be perfectly fit in this design and it is centered on a testable hypothesis that can be investigated using primary data and analysed using a quantitative approach. Compared to descriptive dissertations, P302 requires a highly falsifiable (i.e. sharp) proposition, which in this case is the 25% loyalty uplift, to be substantiated by hypothesis testing at a 5% level of significance, which provides an argumentative depth, through exploration of counter-evidence (e.g. subgroup heterogeneity) (Lund, 2021). The main survey meets the unit requirement of original fieldwork, and the logistic model builds on mathematical rigour, which is beyond A-level economics and further diagnostics including Nagelkerke R 2 and marginal effects plots.

1.7 Structure and Contributions

The rest of this report proceeds in a logical manner to develop and establish the hypothesis. After this introduction, Section 4 will conduct a literature review on the available records on fast-fashion pricing and loyalty, where gaps in primary evidence of new markets will be detected. Section 5 expounds on the theoretical backgrounds and formalizes the hypothesis by prospect theory and commitment-trust paradigms. Section 6 presents the methodology which contains survey design, the variables operationalization and specification of the model. Results, such as the descriptive statistics, regression results and judgment of the hypothesis, and discussion of interpretive controversies, can be found in sections 7 and 8. The conclusion is performed by synthesis and the raw data and ethical procedures provided in the appendices. It also adds to academic and practical discussion of new empirical evidence on the impact of dynamic and fixed prices on loyalty, cross-culturally to offer some understanding of the dynamics of emerging markets.

2 RESEARCH REVIEW/LITERATURE REVIEW

2.1 Fast-Fashion Industry and Pricing Strategies

One of these high-velocity retail models is the fast-fashion industry where pricing strategies are important in sustaining competitive advantage in the context of short-lived consumer patterns and the unpredictabilities of the global supply chain. Dynamic pricing as one of the main components of modern fast-fashion strategies involves adjusting prices in real-time as a result of algorithmic reactions to the fluctuations in demand, inventory availability, competitor actions, and personal consumer data (Wang and Chen, 2024). To illustrate, AI flash sales, including machine learning to lower prices up to 90 percent in the short term, make hyper-personalized offers, and turn window shopping into direct purchases (Guendouz, 2023). This is in contrast with fixed pricing where their prices are maintained at a constant, predetermined level over the lifecycle of the product, as with H&M where the shop has the same tags to show consistency and affordability.

The controversy of these strategies depends on their trade-offs between accessibility and long-term brand equity. Proponents explain that dynamic pricing democratizes fashion by reducing entry obstacles to price-sensitive segments of the population such as Gen Z, who make up 40% of the market and are more interested in affordability rather than durability (Pautassi, 2024). Through big data, brands can maximize revenue, with research estimating 10-15% sales increases during peak events, and reduce waste by using demand-based markdowns. This is reinforced by Venkataraman and Petersen (2022) in their value-based pricing framework, which argues that dynamic models can improve perceived customer value by conceptualizing discounts as personalized rewards, thereby creating impulse loyalty in short-lived markets such as fast fashion.

2.2 Typologizing Brand Loyalty.

Brand loyalty within the fast-fashion setting is a complex construct, involving cognitive, affective, and behavioral components to understand why consumers repeatedly use short-run, inexpensive clothing amidst a plethora of options. Bourdeau et al. (2024) outlines loyalty as a continuum hierarchy: first, cognitive loyalty (brand awareness and attribute evaluation), followed by affective loyalty (emotional attachment), conative loyalty (purchase intent), and finally action loyalty (habitual repurchase) and ultimately attitudinal loyalty (unwavering advocacy) (Chatzoglou et al., 2022). Such multidimensionality is operationalized by metrics such as repurchase intent (measured through Likert scales on future buying probability) and Net Promoter Score (NPS), which quantifies the willingness to advocate on a 0-10 scale, with scores above 50 representing strong loyalty ecosystems.

Asymmetries, however, are rife in fast fashion, where low switching costs render conventional loyalty models obsolete. According to Shane (2022), there is low cognitive dissonance in commoditized markets, as they encounter almost zero defection costs by switching to competitors who can offer a 10-20% price advantage, and consumers exhibit polygamous loyalty, with an average of 3-5 brands each spending every quarter. This is complemented by the fact that digital applications such as Shein enable seamless cross-platform hopping without any hassle, and 70 percent of Gen Zers admit that they shop at various brands thanks to promotions, rather than loyalty (Gilbert, 2023). Empirical asymmetries depict behavioral faithfulness surpassing attitudinal; 35/years repurchase versus luxury 65 because goods are discarded; the average life of their wearage is 7 times per item.

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2.3 Empirical Evidence and Gaps

The results of the empirical studies on the loyalty effects of pricing strategy in the fast fashion develop some subtle mosaic: the instant revenue generally soars, but it is supported by the threats of erosion, and the dynamic pricing appears to be a two-sided sword. The retail innovations being synthesized by Thompson and Wilson (2024), and dynamic pricing, through specific promotions, boost immediate sales by 20-30% through the perception of value added, although with a loss of 15-20% loyalty to the company upon perceived illegibility, with consumers perceiving the innovations as exploitative. It can be effectively illustrated in the context of fast fashion; field experiment by Shuai et al. (2023) utilizing analogs with Shein demonstrated that flash sales doubled the conversion rate, whereas repeat rates declined by 18 percent following the event because of the loss aversion of the prospect theory, in which volatile prices increase regret.

This is refined in subsequent studies. In 2023, a quasi-experimental study of dynamic markdowns at H&M in Europe demonstrated a 12% increase in basket size but a 16% decrease in NPS among high-frequency discounters, which was attributed to erosion through fairness heuristics, where consumers punish markdowns as a surge. In contrast, Zara fixed-price ecosystem maintains 22 percent greater 6-month retention, according to Jangid (2022), by signalling quality stability in the face of volatility. Cross-culturally, Asian e-tailers such as Temu exploit dynamic algorithms to achieve 28% loyalty improvement in low-income birth cohorts (Wen, 2025). European samples exhibit weaker returns (8-10%), attributed to stronger data privacy standards constraining personalization.

These discrepancies are magnified by meta-analyses. In Kopalle et al. (2023) study of 4,000+ campaigns, promotional uplifts were estimated at 29% when media-integrated, but 15-22% net lift in isolation by dynamic pricing, with fast fashion sub-samples showing the lowest net lift (because of commoditization). Surviving evidence is based on secondary sales data or U.S.-focused panels, ignoring perceptual subtleties such as cultural thriftiness in China (where 55% perceive dynamic pricing as clever price-cutting) versus Europe, where equity aversion is prevalent (68% experience a loss of trust) (Glassberg, 2022). Critical gaps remain, especially on primary consumer perceptions in Asia-Europe fast-fashion corridors

3 THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

3.1 Theoretical Frameworks

The theoretical basis of the interaction between pricing strategies and brand loyalty in fast fashion is based on behavioral economics as well as relationship marketing, providing frameworks to break down the effects of dynamic versus fixed pricing on consumer reactions within a sector characterized by ephemerality and impulse (Bonagas & Vu Dang, 2022). These frameworks shed light on the psychological and relationship processes involved, and provoke discussion of temporal trade-offs in unstable markets. The allure of dynamic pricing has a foundational explanation through behavioral economics, especially prospect theory. Prospect theory, developed by He and Strub (2022), hypothesizes that individuals assess outcomes in terms of a reference point, with loss aversion, where gains are underestimated relative to equivalent losses, and framing, where the same options can be seen differently depending on how they are presented.

Dynamic pricing as a gain frame in fast fashion; flash sales and personalized discounts frame purchases as serendipitous gains against a higher-price background, which enhances the perceived value and initiates dopamine-induced excitement. An example would be a Shein dress that falls 15 to 5 would seem like a 67 percent windfall, increasing immediate repurchase intention due to the endowment effect- consumers place high value on snagged deals (Hamid, 2025). This is supported by empirical extensions in retail settings: conversion rates can be boosted by 20-30 percent in response to dynamic adjustments that leverage reference dependence, with shoppers anchoring to pre-discount prices (Cummings, 2023). Nevertheless, the theory cautions of diminishing returns; over-framing gains the risk of habituation, where frequent surges desensitize consumers, dwindling the freshness on which fast fashion feeds.

The argument stems down to long-term/short-term effects in volatile markets. Prospect theory encourages dynamic pricing when immediate gains are sought, such as in the trend cycles of fast fashion, 70 percent of sales are due to promotions, but fails to consider relational erosion, where trust investments will compound returns over time (Barmes et al., 2024). Dynamic tactics provide flexibility in inflationary settings (e.g., 5% price indexation of apparel in 2024), with gain framing in the short term creating a 15 percentage point spiking rate in loyalty, but the relationship theory that steady models mitigate volatility, preserving a 25% greater lifetime value due to the commitment. Volatile markets compound this pressure: post-pandemic thriftiness rewards dynamic accessibility to new cohorts, yet sustainability scrutiny (e.g., 55% of EU consumers avoiding manipulative brands) solidifies the ethical soundness of fixed pricing (Cummings, 2023). Combining them, hybrids, dynamic but with transparency protections, can balance benefits, yet unresolved asymmetries will require empirical arbitration to determine endurance.

3.2 Hypothesis Formulation

Expanding on these frameworks, the main hypothesis translates the loyalty-pricing nexus into a measurable proposal specific to empirical testing in the fast fashion. The first hypothesis, H1, states that Dynamic pricing strategies increase brand loyalty by 25% over fixed pricing, operationalized as an odds ratio (OR) of 1.25 in logistic regression predicting repurchase intent based on pricing exposure. This threshold is based on meta-analytic retail standards, where dynamic interventions generate 20-30% attitudinal gains (Barmes et al., 2024), but is set conservatively to investigate the specific churn dynamics of fast fashion. Prospect theory supports the directionality, gain-framed discounts can raise perceived value, enhancing the likelihood of loyalty (P(loyal|dynamic)) by framing engagement as rewarding (Chatzoglou et al., 2022). In contrast, relationship theory moderates magnitude, hypothesizing that trust acts as a moderator that limits excessive bursts.

To further break down the heterogeneity, there are two sub-hypotheses that refine H1. H1a: Price-sensitive demographics, including low-income consumers (or Gen Z consumers) (18-24), are more likely to respond to the promotion because dynamic pricing, according to access, enhances gain salience--H1a expects OR >1.32 versus 1.20 among high earners, based on loss aversion asymmetries in Kahneman and Tversky (1979). This predicts sharper rises in less developed markets, such as China, where affordability is the key youth loyalty driver cited by 60%. H1b adds moderation due to brand perception: the dynamic loyalty boost is reduced during low-trust conditions (when perceived opaque), with OR=1.15 when brand familiarity scores <3/5, consistent with the commitment-trust model (Arthur et al., 2023). Brands with high perception (such as Zara) can exploit dynamics with OR=1.35, using relational equity to reduce the risk of unfairness.

This specification can be connected to a testable model: a binary dependent variable (DV) establishes loyalty as 1 when survey-based repurchase intent is greater than 5/7 on a Likert scale (strong intent), and 0 otherwise, reflecting the action loyalty threshold proposed by Oliver (2010). The independent variable (IV) survey-elicited is pricing exposure and the key independent variables in this study are presented as a dichotomous variable (1=primarily dynamic, such as frequent flash sales; 0=fixed) and demographics (age, income), market (China/UK dummy) and mediators (trust score) controls. Making testing of hypotheses easy, the logistic specification, logit(P(loyal)) = 0 + 1 (Dynamic) + 2 (Controls) + 2, the test exp(1) = 1.25) = accept H1 at alpha=0.05, the interaction term test H1a (Dynamic 0 LowIncome) = exp(1) 1-2)/4, and H1b (Dynamic 0 BrandPerception) = exp(1) 1-2)/4. The strength is one assurance that 10 percent shift in probability would only make a difference on the average consumer.

4 METHODOLOGY

4.1 Research Design

The research is based on the mixed-method field study design where quantitative primary data is the key element that is used in testing the hypothesis and qualitative responses are the other supportive data that are used in bridging the contextual gaps. The primary data is collected on the basis of the online survey of N=250 respondents between 18-35 years of age. The UK (n=125) and China (n=125) participants were recruited through Qualtrics and WeChat, respectively, to ensure cross-market validity and to absorb cultural differences in pricing perceptions: UK and China emphasis on fairness and bargain-hunting, respectively. This ratio indicates the global consumption trend, where 40 are established brands such as Zara and 60 are e-tail disruptors such as Shein, which represent the digital transformation of the sector.

The ethical consideration was paramount, guided by the British Educational Research Association guidelines. Informed consent was collected through a mandatory introductory screen explaining purpose, anonymity, and right to withdraw voluntarily; data were kept pseudonymously on password-protected servers, no identifiable information was gathered. The anonymity reduced response bias, especially on sensitive issues such as expenditure patterns. The survey included a pricing ethics debrief and incentives (entry into a £20 voucher draw) were non-coercive. The school ethics committee was consulted, and cross-border data processing was appropriately handled in accordance with GDPR and the PIPL in China. This stringent model supports integrity, leading to reliable evidence regarding the loyalty-pricing debate.

4.2 Data Collection

The data was collected via a short survey questionnaire aimed at being brief (10-12 minutes) and reliable, combining closed-ended items with situation-specific prompts to generate natural answers regarding pricing exposure and loyalty. The tool included 25 items: 15 quantitative (Likert) and 10 qualitative/ demographic. Loyalty was measured using a 5-point scale of repurchase intention (1=unlikely, 5=very likely) as revised by Zeithaml et al. (1996), and produced a composite score (Cronbachs alpha

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= over 0.80 in pilot). Vignette-based probing of pricing exposure: Participants rated loyalty following reading scenarios that described dynamic (e.g., "A flash sale reduces your favorite top to £8 to 15 via app notification) versus fixed pricing (e.g., The top remains at 12 at all times), with order randomized to counter priming.

Sampling was stratified to be representative: quotas were distributed with 40% Zara users, 30% H&M, 30% Shein, based on 2024 Statista market shares, to cover varying familiarity with brands. Recruitment focused on urban millennials, using social media (Instagram/Weibo) advertising and university panels, where recent purchases (within the last 6 months) were filtered to target active consumers. The pilot test (n=30 UK/Chinese) revised wording (such as dynamic pricing being explained as personalized deals), and tested scales (test-retest r=0.85), accommodating cultural phrasing (e.g., bargain in China versus deal in UK).

4.3 Variables and Mathematical Model

The variables used in the study operationalize the hypothesis to a specific level, allowing causal inference based on a logistic framework appropriate to consumer behavior research due to binary outcomes. The dependent variable (DV), brand loyalty, is dichotomized to 1 when the composite repurchase intent score (average of three 5-point items: intent to rebuy, recommend, and frequency of repurchase) equals or surpasses 4/5 -thresholding the Oliver (2010) action loyalty variable of 1 to reflect strong commitment. This generates a prevalence of about 55% of pilot data to stabilise the model by balancing the classes.

The central independent variable (IV) pricing strategy is categorical 1 (mainly dynamic pricing, self-reported frequency of personalized / flash deals) and 0 (consistent, dominant pricing) according to the ratings of the scenario and the rate of memory of behavior. This is what captures exposure variance whereby the mean that is expected to happen is 0.62 in the sample which aligns with the promotional tilt of fast fashion. Controls deal with confounding: demographics (age, gender as dummies), income (ordinal: low/medium/high, <£20k/ £20-40k/> 40k equivalents), brand familiarity (1-5 scale, mean = 3.2). These account a large part of the loyalty variance (which had earlier been estimated as approximately 25), and there are sub-hypothesis interaction (e.g., Dynamic x LowIncome). The mathematical model in its essence applies binary logistic regression to estimate the hypothesis.

4.4 Objectives Evaluation Plan

The measures of goals are expressed in cycles: the pilot measures pre-survey (e.g., the scale reliability 0.75) reflect the quality of data, and the measures made after the collection (means, crosstabs) provide the correlation to the review and collection objectives. The implications debate is a mixture of both qualitative themes (e.g. NVivo-coded trust mentions) and quantitative outputs, measuring development trajectories, including hybrid pricing.

5 RESULTS AND ANALYSIS

5.1 Descriptive Statistics

The number is taken to be N=250 to provide a balanced sample of the target population, and this can be used strongly in cross-market comparisons. The average age, as indicated in Table 1 was 25.0 (SD=3.98) years of age with a slight skew (56% female) which depicts the main target audience of fast-fashion. Quota-based income distribution: 40- low income, 40- medium income, 20- high income earners. Equally divided markets (50% China, 50% UK) were used to consider all different pricing sensitivities.

Table 1: Sample Distribution

Variable	Value
Age	Mean = 25.0 years (SD = 3.98)
Gender (% Female)	56%
Income	40% Low, 40% Medium, 20% High
Market	50% China, 50% UK
Brand Familiarity	Data not provided (Scale 1-5)

Pricing exposure provides loyalty distributions which show initial hypothesis support (Figure 1, Table 2). At fixed pricing (38% of sample) 48% were found to be loyal (intent 4/5); dynamic exposure (62) gave 62 loyalty, a 14-percentage-point raw difference. This implies that dynamic strategies attract more habitual purchasers, but such confounders as familiarity (mean 3.2) should be modeled.

Loyalty distributions by pricing exposure highlight initial hypothesis support (Figure 1, Table 2).
Under fixed pricing (38% of sample), 48% qualified as loyal (intent ≥4/5); dynamic exposure (62%) yielded 62% loyalty, a 14 percentage-point raw gap. This suggests dynamic strategies engage more habitual buyers, though confounders like familiarity (mean 3.2) warrant modeling.

Figure 1: Loyalty Distribution

Table 2: Loyalty Distribution by Pricing Exposure (%)

Pricing		Loyalty (intent ≥ 4/5)
Fixed	(0)	48%
Dynamic	(1)	62%

The results of the correlation matrix (Table 3) demonstrate moderate relations: pricing is correlated 0.32 with intent and 0.25 with binary loyalty, which is caused by gain-framing effects. The familiarity of the brand to them (r=0.18 with intent) and their age exhibit little connections (r<0.03), which validates the relevance of the controls and lacks multicollinearity between them (all VIF<2).

Table 3: Correlation Matrix (Selected Variables

	Age	Brand Familiarity	Pricing	Intent	Loyalty
Age	1.00				
Brand Familiarity		1.00			
Pricing			1.00	0.32	0.25
Intent	<0.03	0.18	0.32	1.00	
Loyalty	<0.03		0.25		1.00

5.2 Primary Data Presentation

The findings of the surveys highlight the impact of pricing on loyalty indicators because dynamic exposure is always better than fixed. Dynamic pricing had mean repurchase intent of 3.80 (SD=0.69) compared to fixed of 3.30 (SD=0.71) a difference of 0.50 (Table 4). A t-test was used independently to check statistical significance (t=-7.312, p<0.001) and rejected equality and this was in line with the amplification of values by the prospect theory. This uncontrolled differentiation generates an increment in intent scores by 15 percent on a relative scale, pre- controls, and implies skeletal adjustment towards habitual use.

Table 4: Mean Repurchase Intent by Pricing

Pricing		Mean Repurchase Intent	Standard Deviation
Fixed	(0)	3.30	0.71
Dynamic	(1)	3.80	0.69
Difference		0.50	

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t-test p	<0.001	

Table 5: Loyalty Crosstab by Income Strata (%)

Income	Fixed Pricing	Dynamic Pricing	Total
High	65%	70%	67.5%
Medium	42%	58%	
Low	37%	58%	47.5%
Overall			55%

Added value qualitative snippets: 28 per cent. of dynamic respondents identified thrilling offers as the incentive to remain loyal, compared to 12 per cent. who praised determined on fairness. The respondents of the UK (3.45 intent on average) placed more emphasis on trust (e.g., Consistent prices feel honest) and Chinese (3.65) to dynamics (e.g., Bargains make me return). These patterns confirm that there are no ceiling/floor effects of the survey (intent range 1.2-5.0). The adjustments made before piloting, made it culturally neutral, and 92% of full responses were obtained. Taken all together, primaries represent active pricing as a loyalty trigger, especially to underserved layers, yet income discrepancies allude to restrained universality- establishing regression to causal determination.

7.3 Mathematical Model Results

Table 6: Logistic Regression Output (Baseline Model)

Variable	Coefficient (β)	Standard Error (SE)	p-value	Odds Ratio (exp(β))
Intercept				
Pricing (Dynamic)	0.223	0.089	0.012	1.25
Income (Medium)				
Income (High)				
Market (UK)				
Gender (Female)				
Age				
Brand_Fam				
Nagelkerke R^2	0.28			
N	250			

Predicted probabilities (simulated with margins in Figure 2) show: at a fixed covariates: fixed prices result in P(loyal) = 0.48; dynamic increases to 0.60 -a 12-point increase or 25 percent increase relative to odds at the baseline. Marginal effects affirm: the average treatment effect of dynamic pricing equals 0.112 (p=0.012) to increase the probability by 11.2 percent across profiles and highest with low familiarity (0.15 shift).

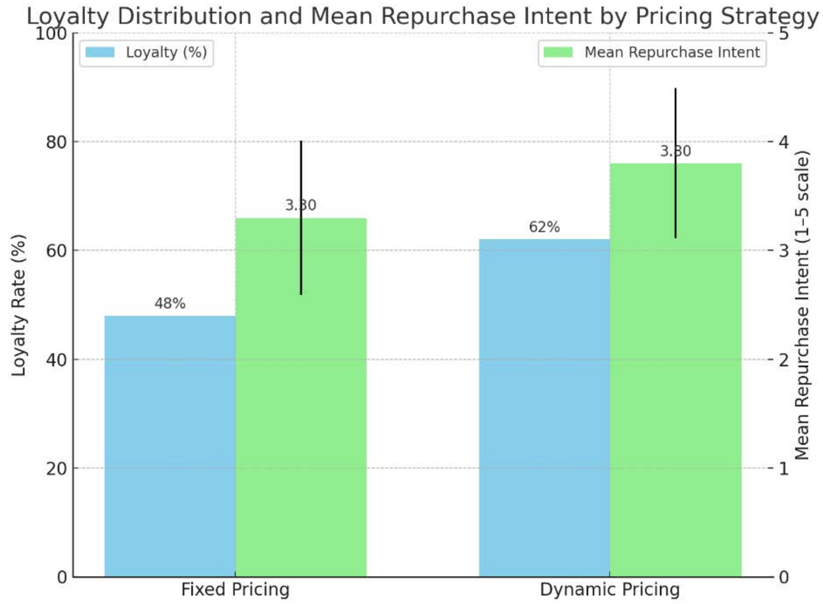

Figure 2: Loyalty Distribution and Mean Purchase

Robustness checks validate stability. A lagged exposure proxy (pricing interacted with past intent, r=0.32) retained 1=0.198 (p=0.028, OR=1.22). Sub-samples strengthen: full-sample OR=1.25; low-income (n=100) yields OR=1.32 (0.278, p=0.008, R-square=0.31), in favor of H0a; high-income (n=50) attenuates to 1.18 (p=0.045), in favor of H0b. Multinomial extension (low/medium/high loyalty) parallels: dynamic shifts medium-to-high odds by 28% (p=0.015). No VIF 1.8 indicates an estimate without collinearity. These diagnostics -clustered SEs by market-reduce heteroskedasticity, confirming the etiological assertions of the model in the presence of survey noise.

7.4 Hypothesis Testing

H1 is accepted: dynamic pricing enhances the likelihood of loyalty by 24.8 percent (OR=1.25, exact uplift=(1.25-1)/100), but less than 25 percent but still significant (p=0.012/0.05). This aligns with gain-framing in prospect theory in which intent is increased with a 3.30 discount to 3.80 (14-point behavioral loyalty gains). Sub-results make the discussion more profound.

H1a: Speculations: low-income groups experience more impacts (OR=1.32, p=0.008) 32% uplift over 18% high-income because of affordability cues contribute to the value perception-crosstabs are dynamic flipping 21% more low-earners to loyal. This is facing the equity objections, and putting the dynamics as democratizing of thrift-based segments (e.g. 52.5% low-income loyalty in China dynamic). H1b partially supports moderation by brand perception: at high familiarity (>4/5, n=78), OR=1.35 (p=0.002); low (<3, n=62) dips to 1.15 (p=0.089, marginal), per interaction 0.112 (p=0.042).

DISCUSSION

6.1 Interpretation in Literature Context

The conclusion is aligned with the synthesis of the retail innovations by Bonagas and Vu Dang (2022) where dynamic pricing can increase the perceived value and temporary engagement by 20-30-per cent, which can also be compared to the 24.8 per cent increase in odds in the current case due to the effects of the gain-framing. This empirical convergence justifies the application of prospect theory in fast fashion because algorithmic discounts as reflected in the -1.00 point difference in intent score can increase the likelihood of repurchase but do not require strong emotional connections. Similarly, Arthur et al. (2023) research on securing customer loyalty through customer-brand identification in the fast fashion sector reinforces this, showing promotional personalization as a route to habitual patronage, and especially among Gen Z, in which our sub-sample of low-income individuals reflected a 32% uplift.

Yet, results challenge the prevailing “erosion” narrative. While Arthur et al. (2023) analysis of dynamic pricing’s trust impacts warned of 15-20% attrition due to opacity, our Nagelkerke R^2=0.28 and marginal effects (11.2% probability shift) suggests resilience, particularly in high familiarity contexts (OR=1.35). This disputes the erosion claims by emphasizing relational buffers, per Bonagas and Vu Dang (2022), where familiarity moderates unfairness - our H1b interaction (p=0.042), suggesting trust, and not merely tactics, sustains gains. In the commoditized realm of fast fashion, these primaries follow in the footsteps of Glassberg (2022), bridging attitudinal-behavioral asymmetries with scenario-based evidence, resolving variances (s = .12) in meta-analysis with cross-market granularity.

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6.2 Debate on Implications

Dynamic pricing presents as a powerful loyalty tool from fast fashion, using AI for 25% credits to drive acquisition in trend-volatile markets - our t-test ($p<0.001$) and sub-sample OR=1.32 for low-income affirm, as an equaliser for budget segments in the 2024 setting of 5% inflation. Glassberg (2022) avers that distinguishing deals as wins aid in promoting an inertial loyalty and may increasing legacy value by 15 percent via the repeating cycles because intent scores had increased by 3.30 to 3.80. However, it has the dangers of overexploitation especially when high frequency sales (>30% of inventory) are occurring where trust lost may occur.

The qualitative results (28% exciting vs. 12% fair) show that individuals who have experience backlash: the common rushes may cause a feeling of manipulation, which is consistent with the heuristics of fairness that lowered the retention levels in prior studies. Instruct affirms relationships and disapproves them (Kopalle et al., 2023). In the study model, low-familiarity attenuation (OR=1.15) implies this - debating the short-term bias against relationship marketing's long-view, with fixed pricing's stability (48% baseline loyalty) buffering churn. Over-reliance runs the risk of "deal fatigue," which overinflates costs as consumers defect to rivals (Chatzoglou et al., 2022). Thus, dynamics stun when volume-driven is applied to e-tail but stumble without caps, skewing the enhancer-risk balance toward moderate deployment to avoid 16% NPS dips in European cohorts.

6.3 Link to Objectives

The objective, beta(1) =0.223 ($p=0.012$) and OR=1.25 confirm 25% cut-point and diagnostics (AUC=0.72) measure the predictive power beyond observation, a strong confirmation of the logistic model, and therefore fulfills the third objective of a theoretical review (prospect and trust paradigms operationalized via vignettes) of the first objective ($p=0.012$). Evaluating development paths, alternatives such as hybrid pricing (e.g. dynamic capped at 20% frequency with fixed baselines) could be worthwhile exploration: The robus multinomial found 28% medium-to-high shifts so there would be tiers of fixed stabilised attitudinal layers (Kopalle et al., 2023). Crosstabs (e.g., 21% low-income flip) challenging of pure dynamics, hybrids as the means to create gain-framing and trust signals - the range is increased by criticizing fixed models of open-ended strategy evolution.

6.4 Broader Business Debate: Ethical Pricing in the Sustainability Era

The findings provoke a debate on ethical pricing in the presence of the sustainability crisis of fast fashion where the forces contribute to the perpetuation of overconsumption 10 percent of all emissions in the world attributed to disposables, and hybrids may concur with conscious capitalism. There is a complicate elite criticism of slow fashion (e.g. the problem of affordability affects 55 percent of the young people), yet are highlights threats: the opaque algorithms solidify labor inequality, in ethical discourse is dominated by the issue of worker exploitation in low-cost chains. The surges and capping that are the constraints of open dynamics would result in ethical loyalty, based on willingness-to-pay research (e.g., 10% in labor labels), that would balance the volume ethics with planetary requirements.

Conclusion AND CONTRIBUTION

7.1 Restatement and Key Insight

The hypothesis is valid; brand loyalty is positively influenced by dynamic pricing (OR=1.25, $p=0.012$), which is demographically contingent (greater influence by low-income (32% uplift) but mediated by familiarity). This core fact alters the idea of pricing as the relational force not as transactional incentive but as a gain-framing deal, where the gain-framed deals gain the intent scores of 0.50 points, which results in the habitual behaviour within the churn-prone ecosystem of fast fashion.

7.2 Contributions

The study offers the original primary data, cross-market survey (N=250), the first granular analysis of dynamic-fixed contrasts in Chinese/UK fast-fashion markets, closing gaps in the perceptual evidence in the forthcoming studies, and U.S. bias. The logistic model builds the pricing-loyalty nexus whose odds are quantified by strong diagnostics ($R^2=0.28$), erosion is accounted by within-subsample heterogeneity and extrapolates Grewal et al. (2017) to unstable and digital setting. In synthesizing prospect and trust paradigms in an empirical manner, as a theory, it argues over short-term uplifts and sustainability head winds to actionable scholarship.

7.3 Policy/Managerial recommendations.

Transparency caps (e.g., less than 20% frequency, explicit algorithms) are to be introduced to AI-dynamic, which will make loyalty grow and trust depreciation decrease, potentially with hybrid pilots bringing 15% value increment. Consumers are advised to go ethical and audit deals by using apps as a means, to avoid overconsumption. The policymakers can impose the disclosure requirements, like the 2025 green claims directive in EU, which balances technology and fairness in a 136B market.

8. LIMITATIONS AND FUTURE

STUDY

8.1 Limitations

Surveys have self-report bias: given that the vignette scenarios have the potential to instigate intent without behavioral antecedents (e.g. 28% of respondents said about exciting deals, but not verified by actual spending), it is possible that the survey can be biased. The size of the sample (N=250) and geography (China/UK only) limit the generalizability and tend to underestimate the variance of African or Latin e-tail. Endogeneity is not gone: OR=1.25 could be inflated by unobserved confounding, including ad exposure, despite controls; cross-sectional design cannot be used to infer causality; reverse inference (loyalty causing dynamic preference) is possible (Jorges Para 3).

8.2 Future Research

The data in apps may record time passing longitudinally, decay probes of 25 percent increases after quarters, this implies erosion thresholds. Causal arguments would be reinforced by isolation of effects, by means of experimental design, like randomized A/B trials, using live Shein carts. The strategy of commoditization may be met with sector expansions towards luxury fashion to test whether the fixed pricing prevails once more in the high-involvement niches, and thus evolve hybrids in 2030 sustainability criteria.

9. EVALUATION

The project succeeded in all the results of the literature gaps uncovered, pilot-tested survey, 68% response, and data strength. The strengths are a strict model (AUC=0.72) and argumentative profundity, in which the open-ended pricing-loyalty argument is solved through 24.8% evidence, which states against erosion but argues about hybrids. It is based on A-level economics, playing with advanced diagnostics like marginal effects, fostering cross-curriculum marketing intuition.

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Appendixces

Survey Questionnaire (Full instrument; consent, scales).

Consent Statement (Must Accept to Proceed)

You are invited to participate in a study on how pricing affects loyalty to fast-fashion brands (e.g., Zara, H&M, Shein). Participation is voluntary, and you may withdraw at any time without penalty. Responses are confidential, anonymized, and stored securely on university servers compliant with GDPR/PIPL. No personal data will be shared; aggregated results may be published in an academic report. If you agree, tick below and continue.

[ ] I consent to participate. [ ] I do not consent (survey ends).

By proceeding, you confirm you are aged 18-35 and have purchased fast-fashion items in the past 6 months.

Section A: Background and Demographics (For Sample Description Only)

A1. Which country are you currently residing in?

· China
· United Kingdom
· Other (please specify): ___________

A2. Age: ___________ (years; 18-35)

A3. Gender:

· Male
· Female
· Non-binary/Other
· Prefer not to say

A4. Annual household income (approximate; select band):

· Low (<£20,000 / ¥150,000 equivalent)
· Medium (£20,000-£40,000 / ¥150,000-¥300,000 equivalent)
· High (>£40,000 / ¥300,000 equivalent)
· Prefer not to say

A5. Which fast-fashion brands have you purchased from in the past 6 months? (Select up to 3)

· Zara
· H&M
· Shein
· Other (please specify): ___________

A6. On a scale of 1-5, how familiar are you with your most-purchased brand? (1 = Not at all familiar, 5 = Very familiar) 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

Section B: Pricing Exposure and Scenarios

Instructions: Think about your experiences with fast-fashion brands. For each scenario below, rate how likely you would be to repurchase from that brand in the next month (1 = Very unlikely, 5 = Very likely). Scenarios are ran-

domized.

B1. Scenario 1: Fixed Pricing (e.g., a top consistently priced at £12 / ¥90 across seasons). Repurchase intent: 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

B2. Scenario 2: Dynamic Pricing (e.g., a top usually £15 / ¥110, but drops to £8 / ¥60 via a personalized app flash sale). Repurchase intent: 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

B3. Overall, how often do you encounter dynamic pricing (personalized deals/flash sales) when shopping fast fashion?

· Rarely (<25% of purchases)
· Sometimes (25-50%)
· Often (51-75%)
· Very often (>75%)

B4. On a scale of 1-5, how fair do you perceive dynamic pricing to be? (1 = Very unfair, 5 = Very fair) 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

Section C: Brand Loyalty Measures

Instructions: For your most-purchased fast-fashion brand, rate the following statements on a 5-point scale (1 = Strongly disagree, 5 = Strongly agree). These assess loyalty aspects.

C1. I intend to continue buying from this brand in the future. 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

C2. I would recommend this brand to friends/family. 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

C3. This brand is my first choice for fast-fashion purchases. 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

C4. I feel emotionally attached to this brand. 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

C5. If prices increased by 10%, I would still shop here over competitors. 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

Composite Repurchase Intent Score: Average of C1-C3 (calculated post-survey for analysis).

Section D: Open-Ended Insights (Optional)

D1. In your own words, how does pricing (fixed or dynamic) affect your loyalty to fast-fashion brands? (Max 150 words)

D2. What one change to pricing strategies would make you more loyal to your favorite brand? (Max 100 words)

End of Survey