ISSN XXXXX (PRINT) | ISSN XXXXX (ONLINE)

OPEN ACCESS

Continental Academic Journal of Integrative Research and Studies (CAJIRS)

Abbreviated key title: Contin. Acad. J. Integr. Res. Stud.

Journal home page: https://Continentalacademicpublisher.com/journal/cajirs



Algorithmic Pricing in Emerging E-Commerce Markets: The Roles of Price Sensitivity, Digital Literacy, and Consumer Trust

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ABSTRACT RESEARCH ARTICLE

Algorithmic pricing – the data- and conditions-driven automation of retail prices via software is quickly evolving into common infrastructure in online commerce, yet its psychological aspects from the consumer side have not yet been thoroughly specified, especially in emerging markets where price competition is fierce, digital competencies are distributed unevenly, and institutional trust is relatively weak. Based on the theories of price-fairness and organisational trust, this study proposes and examines a moderated serial mediation model that shows how perceived exposure to algorithmic pricing negatively affects purchase intention through reducing the perceived price fairness and thus consumer trust. Price sensitivity has been theorised to be a factor that aggravates this fairness erosion, while digital literacy has been theorised to be a factor that acts as a buffer to this trust erosion. Path analysis with regression-based and 5,000 bootstrap resamples was performed on survey results from 612 online consumers in Bangladesh. Exposure had an indirect effect through fairness ($\beta = -0.23$) and trust ($\beta = -0.24$) that jointly mediated the effect to purchase intention (total indirect effect = −0.19, 95% CI [−0.24, −0.14]) while the direct effect was not different than zero. The exposure–fairness link became stronger ($\beta = -0.10$) and the exposure–trust link became weaker ($\beta = +0.10$) with the influence of price sensitivity, resulting in a conditional indirect effect that differs by a factor of 2.5 across the literacy distribution. The results shift the discussion on algorithmic pricing from one of competition policy to one of consumer capability, and suggest that interventions to increase transparency will under-serviced the consumers most vulnerable to algorithmic pricing.

Keywords: *algorithmic pricing; dynamic pricing; price fairness; consumer trust; digital literacy; price sensitivity; emerging markets; e-commerce*

Citation: Ahnaf, M. A., Tahira, K. T., Sani, M. A. I., Islam, F., Bonik, A., Mannan, S. I., Sifat, M. O., Mukta, M. I., Sunbeam, I. F., Tasneem, A. T., & Antmonitoail, R. (2026). Algorithmic pricing in emerging e-commerce markets: The roles of price sensitivity, digital literacy, and consumer trust. *Contin. Acad. J. Integr. Res. Stud., 1*(1), 1–16.

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1. INTRODUCTION:

Retail prices are more and more being produced than posted. In grocery stores and ride-hailing apps, prices are dynami-cally determined by software that will process the demand signal, inventory, feeds from competitor prices, and individual buyer histories and adjust the price displayed to each customer in a matter of seconds (Stucke &Ezrachi, 2016). It's no longer just for the high-tech incumbents: repricing tools in the software-as-a-service category have been spread among small third party sellers, like Amazon or Daraz, and a price may now be displayed on a product's page without any con-scious decision-making by any human.

Studies of the impact of this change have made most progress on the supply side. Economists have recorded an increase in prices when algorithmic traders are introduced in retail gasoline markets (Assad et al., 2024a), that pricing algorithms that respond to the actions of rival firms can lead to higher margins than the competitive benchmark (Brown et al., 2023), and that reinforcement-learning agents can reach supra-competitive outcomes without being programmed to communi-cate with rival firms (Calvano et al., 2020). Algorithmic pricing is therefore, for the most part, a competition and collu-sion issue, and thus has been approached as such by legal scholarship (Ezrachi et al., n.d.). In the parallel marketing liter-ature, two themes have focused on the personalisation and its privacy costs: conditioning offers on individual data shifts the distribution of surplus between firms and consumers (Acquisti& Varian, 2005); and perceived privacy invasion harms customer and firm performance (Martin et al., 2017). What's lagged behind is an understanding of what consumers make of an algorithmic price. This is a significant oversight. A visibly contingent price is not just a price that is at or near the bottom of a distribution; it is a statement about the way the seller thinks about her. The price-fairness research literature has long documented that consumers not only compare prices with costs, but with comparison standards and dual-entitlement norms as well (Kahneman et al., 1986); and that deviations from the comparison standards and dual-entitlement norms elicit emotional and behavioural responses that are disproportionate to the monetary cost or benefit at stake (Bolton et al., 2003). Trust research in turn, has demonstrated that e-commerce viability depends on consumers' belief in a vendor's ability, benevolence and integrity (Gefen et al., 2003). If algorithmic pricing is interpreted as a viola-tion of fairness, it should therefore be interpreted as a violation of trust, and trust is the immediate cause of most online purchase decisions (Pavlou & Fygenson, 2006).There are two limitations of the consumer-side evidence that does exist. First, it is overwhelmingly experimental, pitting an ‘algorithmic’ label against a ‘human’ label in vignette settings; it has yielded a contested picture in which, sometimes, people discount algorithms after seeing errors (Dietvorst et al., 2015) and, sometimes, they prefer them outright (Logg et al., 2019), depending on the task and on whether the decision is per-ceived as affective or objective (Longoni et al., 2019). These designs work great for clearly marking the mechanism but are not great for everyday shopping when there is no label and the mechanism must be guessed at by the algorithm. Se-cond, nearly all of this research was done in high-income economies in which there are well-established consumer-protection regimes and relatively high levels of consumer trust in platforms. However, there is disagreement on exactly what dimensions should drive the response: there is a wide disparity in the level of competition, overwhelmingly based on price and not service or brand (marketing & 2011, 2011); the dispersion of digital skills is high because a large propor-tion of shoppers were onboarded during the one-decade diffusion of the smartphone Hargittai, E. (2002); and there is little institutional trust in redress, as people routinely pay cash on delivery. In these circumstances the meaning of the same price algorithm can be quite different, and the "edge" behavior of consumer response can be more important than the average behavior. This study thus poses three questions. First, does perception of exposure to algorithmic pricing di-minish consumer willingness to purchase, and does it do so by lowering the perceived price fairness and thus consumer trust? Secondly, to the extent that there is fairness erosion, is it magnified when a consumer is sensitive to the price she pays? Third, does a capacity to read the mechanism by which a platform produces what it displays—what has been termed digital literacy—cushion the blow of the trust loss? Using survey data from 612 online shoppers in Bangladesh, where e-commerce is rapidly expanding on the back of mobile internet diffusion, but consumer-protection infrastructure is underdeveloped and most online transactions are still completed by cash on delivery, we answer these questions. We propose a moderated serial mediation model in which exposure is passed on to purchase intention through price fairness and trust.

The paper has three contributions. In principle, it recasts algorithmic pricing as a property of markets that consumers in-terpret and sets out the interpretive chain – fairness, then trust – between an opaque pricing practice and a behavioural outcome. This is alongside competition-focused narratives which view consumer harm as an "inevitable by-product of higher prices. Second, it finds two boundary conditions that pull in opposite directions and that represent different theory-based logics, namely stake, which increases the accessibility of fairness norms, and capability, which shifts the attribution a shopper makes for a price difference. The practical implication is that the platform managers are most worried about the loss of trust among those shoppers that are least able to rationalise the price that they see. Third, the study provides a val-idated measure of perceived algorithmic pricing exposure and conditional effect estimates from a market underrepresent-ed in the literature, enabling the moderators to be analysed over a realistic range, rather than being limited to a conven-ience sample of students.

2. METHODOLOGY

2.1 Research Context -

The study was conducted in Bangladesh, an emerging e-commerce market characterized by the fast spread of

platforms and weak consumer-protection infrastructure. By 2025, Internet subscriptions totaled about 136 million, with the majority of these accessed via mobile networks (Bangladesh Telecommunication Regulatory Commission [BTRC] 2025), and the retailers selling on the marketplaces and social-commerce platforms compete for a first-generation online population. The context has 3 aspects that make it appropriate to the research question. Given that the differentiation of platforms with regard to service quality, returns and delivery reliability is limited, price is the most important competitive variable. Digi-tal skills are ubiquitous and unevenly distributed with the majority of shoppers having their first digital device capable of online access in the last 10 years. Trust is expressed transactionally: cash on delivery is the predominant mode of pay-ment, which means that consumers can go for the goods only after the items are physically examined. It is clear from this marketplace that algorithmic pricing is indeed there, but the results of this algorithmic pricing, such as marketplace re-pricing tools or app-only discounts, delivery-fee personalisation, are not often clearly disclosed, meaning that consumers must rely on indirect cues to infer it.

2.2 Sample and procedure

A structured, self-administered questionnaire was used for data collection via online and intercepts in Dhaka and two divisional cities. The respondents were adults (18 years of age and older) who made at least one online purchase in the past six months. The sample was evened out using quotas for age band and gender to ensure that it was not dominated by the student population that is more likely to respond to an online survey. Sixty-one percent of the people who answered the questionnaire (612 of 659) did not straight-line, did not complete in less than one third of the median time, or were unable to pass two embedded attention checks and were included in the analysis. These were not coerced; there was no personally identifying information collected and the respondents were debriefed about the purpose of the study.

The composition of the samples is shown in table 1. The sample is gender balanced (53.6% male, 45.6% female), young-er adults (69.0% aged 18-34), well-educated with 46.6% holding a bachelor's degree and 33.0% a master's degree and spread across income bands. Marketplace shopping (28.6%) and social commerce (29.2%) are the two dominant chan-nels, fashion (30.2%) and grocery (20.1%) are the two dominant categories, and cash on delivery (56.2%) is the domi-nant payment mode, which is in line with the above-described transactional nature of the market.

Table 1: The composition of the samples Sample profile (n = 612)

Characteristic	Category	n	%	Characteristic	Category	n	%
Gender	Male	328	53.6	**Primary platform**	Daraz	175	28.6
	Female	279	45.6		Social commerce	179	29.2
	Other	5	0.8		Chaldal	60	9.8
Age (years)	18–24	206	33.7		Pickaboo	42	6.9
	25–34	216	35.3		Bikroy	57	9.3
	35–44	120	19.6		Other	99	16.2
	45+	70	11.4	**Main category**	Fashion	185	30.2
Education	HSC or below	102	16.7		Electronics	105	17.2
	Bachelor	285	46.6		Grocery	123	20.1
	Master	202	33.0		Beauty	91	14.9
	Other	23	3.8		Home	62	10.1
Monthly income (BDT)	<25,000	119	19.4		Other	46	7.5
	25,000–50,000	179	29.2	**Purchase frequency**	Less than monthly	98	16.0
	50,001–100,000	175	28.6		Monthly	235	38.4
	>100,000	139	22.7		Weekly	183	29.9
Payment mode	Cash on delivery	344	56.2		Several times a week	96	15.7
	Mobile wallet	150	24.5				
	Card	76	12.4				
	Bank transfer						

Notes: *Percentages may not sum to 100 because of rounding. Subgroup reliability: Cronbach's alpha ranges from 0.856 (APE) to 0.881 (TRU) among men and from 0.808 (PS) to 0.886 (PI) among women; the trust–intention correlation is 0.562 among men and 0.521 among women*.

2.3 Measures

The items that measured perceived algorithmic pricing exposure (APE) were created based on the conceptual work of Acquisti and Varian (2005) and the description of marketplace repricing in (Chen et al., 2016); all were measured on sev-en-point scales ranging from 1 (strongly disagree) to 7 (strongly agree); all items are reported in Appendix A. The per-ceived price fairness (PF) was assessed by four items that were adapted from the literature on fairness (Xia et al., 2004). Consumer trust (TRU) was assessed using four items adopted from which included the constructs of ability, benevo-lence, integrity and dependability. Four items were adapted from to measure price

sensitivity (PS). Digital literacy (DL) was assessed using five items adapted from van Deursen and van Dijk (2014) and Ng (2012) that measured information-al, strategic and protective skills. Three items adapted from(Zeithaml et al., 1996) and (Pavlou et al., 2006) were used to measure purchase intention (PI).

The instrument was developed in English and translated into Bangla by two bilingual researchers and back translated by one researcher and committee reconciled. The pre-test was conducted with 30 shoppers and five e-commerce practition-ers to evaluate the content validity; two APE items used technical terms, which was reworded. Questionnaire blocks were randomized and attention checks were placed after blocks 3 and 6.

2.4 Common method variance

Due to all measures being self-reported and collected at one time, procedural and statistical remedies were implemented following (Podsakoff et al., 2003). Questionnaire items were presented as a combination of predictor and criterion blocks; the questionnaire was anonymous in nature and the items were not bipolar or double barreled. The three tests were conducted statistically. The first component of Harman's single-factor test on the 24 items explained 22.97% of the variance, less than the 50% recommended criterion. All variance inflation factors were below the 3.3 threshold, with a full collinearity assessment showing values between 1.04 and 1.56, which are all well below the threshold. Lastly, the results of the test of the discriminant validity of the measurement model (Section 4.1) indicate that no pair of constructs shares a variance that is close to the square of the average variance extracted. Common method variance is unlikely to explain the pattern of results, however, and cannot be ruled out as a partial explanation for the magnitude of some of the coefficients.

2.5 Estimation strategy

The one factor principal axis solution per construct was used to assess the quality of the measures, as were Cronbach's alpha, composite reliability and average variance extracted, while the Fornell–Larckercriterio and the heterotrait–monotrait ratio of correlations(Henseler et al., 2015) were used to assess discriminant validity. Standardised construct scores were used to estimate structural relationships by regression-based path analysis that for a recursive model with reflective composites results in path coefficients identical to a saturated partial least squares structural model, but also enables the estimation of conditional indirect effects. Control variables in all the endogenous regressions were age, edu-cation, gender, income band and purchase frequency. Indirect and conditional indirect effects were evaluated with 5,000 bootstrap resamples and percentile confidence intervals (MacKinnon et al., 2004; Preacher & Hayes, 2008) and modera-tion was explored at one standard deviation above and below the mean score of the moderator (Preacher & Hayes, 2008). Effect sizes are reported as Cohen's f^2 (Cohen, 1988) and out-of-sample predictive accuracy as Q^2 obtained from ten-fold cross-validation (Shmueli et al.,2016).

3. RESULTS

3.1 Measurement model

Table 2 presents the item loadings and reliability of the constructs. All 24 standardised loadings are greater than 0.65 and 21 of 24 are greater than 0.70; the lowest loadings are for the fourth price-sensitivity and the fourth exposure items. All constructs have Cronbach's alpha values above 0.70 and composite reliability above 0.70, and average variance extracted above 0.50, which are above the conventional thresholds. Construct ranges from 4.33 (PF) to 5.19 (PS), which suggests that respondents' fairness perceptions are moderate, trust is moderately strong, and there is a strong orientation to price comparison. Skewness and kurtosis for all constructs are below ±0.40, which is within acceptable limits given the as-sumption of approximate normality in using maximum-likelihood-style estimation.

Table 2: Constructs, item loadings and measurement properties

Construct and item	λ	α	CR	AVE
Algorithmic pricing exposure (APE)		0.858	0.860	0.607
APE1	0.842			
APE2	0.828			
APE3	0.758			
APE4	0.677			
Perceived price fairness (PF)		0.873	0.874	0.636
PF1	0.865			
PF2	0.814			
PF3	0.760			
PF4	0.745			
Consumer trust (TRU)		0.878	0.880	0.648
TRU1	0.888			
TRU2	0.820			
TRU3	0.765			
TRU4	0.737			
Price sensitivity (PS)		0.833	0.835	0.560
PS1	0.790			
PS2	0.803			
PS3	0.736			
PS4	0.655			
Digital literacy (DL)		0.867	0.869	0.571
DL1	0.843			
DL2	0.789			
DL3	0.728			
DL4	0.694			
DL5	0.714			
Purchase intention (PI)		0.873	0.875	0.700
PI1	0.891			
PI2	0.845			

PI3	0.770			

Notes: *λ = standardised loading from a one-factor principal axis solution; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Item wording is reported in Appendix A.*

On both criteria, the discriminant validity is satisfactory (Table 3). Each square root of the AVE is greater than the equat-ed off-diagonal relationships for all of the constructs, and the highest heterotrait–monotrait correlation relationship is 0.62 between trust and intention, which is well below the conservative cut-off value of 0.85. The highest correlation on the matrix is between trust and purchase intention (r = 0.54) as is theoretically expected and does not pose a problem for the discriminant validity with the composite reliability. Reliability and the HTMT matrix are summarised graphically in Figure 2

Table 3: Discriminant validity: Fornell–Larcker criterion and heterotrait–monotrait ratios

Construct	APE	PF	TRU	PS	DL	PI
APE	**0.779**	0.267	0.330	0.074	0.210	0.186
PF	−0.231	**0.797**	0.396	0.007	0.054	0.408
TRU	−0.287	0.347	**0.805**	0.034	0.072	0.621
PS	0.062	0.005	−0.029	**0.748**	0.229	0.004
DL	0.180	−0.046	0.063	0.194	**0.756**	0.060
PI	−0.162	0.356	0.544	0.004	0.052	**0.837**

Notes: *Diagonal (bold) reports the square root of the average variance extracted. Below the diagonal: construct correlations. Above the diagonal: absolute heterotrait–monotrait ratios. All correlations with $|r| \geq 0.08$ are significant at $p < 0.05$*

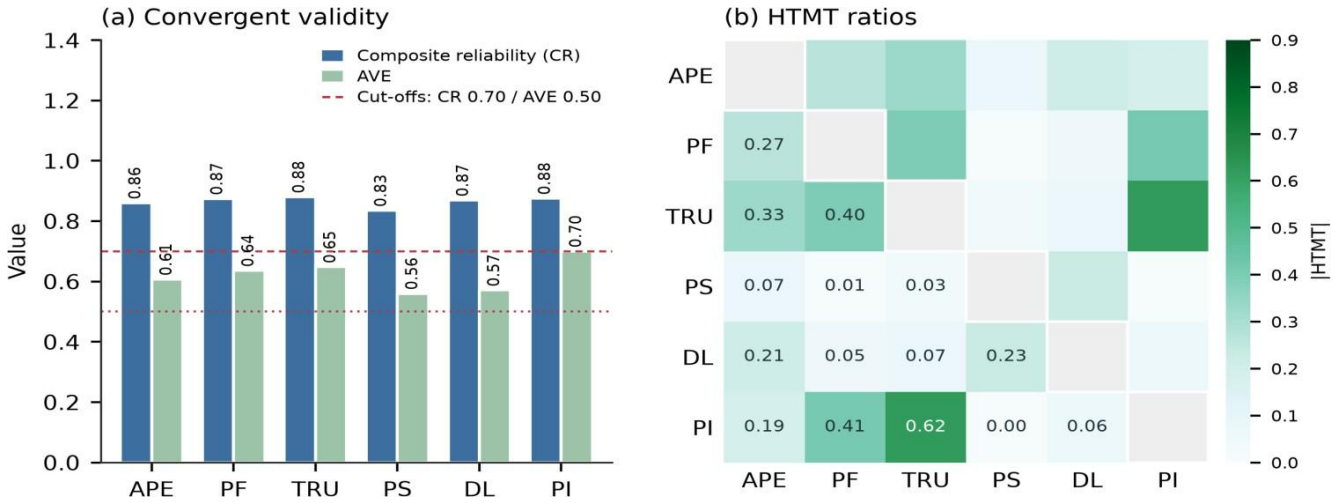


Fig. *2.* Measurement model quality. Panel (a) reports composite reliability and average variance extracted against conventional cut-offs; panel (b) reports absolute heterotrait–monotrait ratios, with the 0.85 threshold of concern.

3.2 Structural model

Table 4 reports descriptive statistics and collinearity diagnostics, and Table 5 reports the structural estimates. The model accounts for 7.5% of the variance in perceived fairness, 19.5% of the variance in trust and 33.2% of the variance in purchase intention, while the cross-validated Q2 values are 0.044, 0.160 and 0.313, respectively, and all are above zero, in-dicating out-of-sample predictive relevance. Multicollinearity does not seem to be an issue as variance

inflation factors in each equation vary between 1.00 and 1.21; although the constituent scores were standardised, the interaction terms were mean-centred prior to being multiplied together.

Table 4: Descriptive statistics and collinearity diagnostics

Construct	Mean	SD	Skewness	Kurtosis	VIF
APE	4.61	1.07	−0.10	−0.38	1.16
PF	4.33	1.12	−0.04	−0.38	1.22
TRU	4.92	1.07	−0.22	−0.32	1.56
PS	5.19	0.98	−0.32	−0.23	1.04
DL	4.73	1.04	−0.03	−0.39	1.09
PI	5.12	1.11	−0.35	−0.36	1.49

Notes: Composites scored on the original 1–7 metric. VIF = construct-level variance inflation factor from the full collinearity assessment (Kock, 2015); the threshold of concern is 3.3.

Exposure is negatively associated with perceived fairness ($\beta = -0.229$, $t = -5.79$, $p < 0.001$, $f^2 = 0.056$), supporting H1. Fairness is positively associated with trust ($\beta = 0.290$, $t = 7.68$, $p < 0.001$, $f^2 = 0.098$), supporting H2. H3 is supported in partial mediation: The direct path from exposure to trust is negative ($\beta = -0.235$, $t = -6.09$, $p < 0.001$, $f^2 = 0.062$); the indirect path from exposure to fairness to trust is also negative and significant ($\beta = -0.067$, 95% CI [−0.101, −0.041]). Trust is by far the most significant factor affecting purchase intentions ($\beta = 0.485$, $t = 13.25$, $p < 0.001$, $f^2 = 0.291$), lend-ing some support to the first clause of H4. The direct link between exposure and intention is almost nonexistent ($\beta = 0.022$, $t = 0.62$, $p = 0.533$, $f^2 = 0.001$) after the mediators are added to the model, as suggested by the full mediated path from exposure to intention via the fairness–trust chain.

Table 5: Structural model estimates (standardised)

Relationship	β	SE	t	p	f^2	Hypothesis
APE → PF	−0.229	0.040	−5.79	<0.001	0.056	H1
PF → TRU	0.290	0.038	7.68	<0.001	0.098	H2
APE → TRU	−0.235	0.038	−6.09	<0.001	0.062	H3
TRU → PI	0.485	0.037	13.25	<0.001	0.291	H4
PF → PI	0.195	0.036	5.42	<0.001	0.049	—
APE → PI	0.022	0.035	0.62	0.533	0.001	—
PS → PF	0.005	0.040	0.13	0.896	0.000	—
DL → TRU	0.116	0.037	3.12	0.002	0.016	—
APE × PS → PF	−0.103	0.041	−2.50	0.013	0.010	H5
APE × DL → TRU	0.101	0.037	2.75	0.006	0.013	H6

Notes: *n = 612. β = standardised coefficient; f^2 = Cohen's effect size. Model fit: R^2 = 0.075 (PF), 0.195 (TRU) and 0.332 (PI); Q^2 from ten-fold cross-validation = 0.044, 0.160 and 0.313 respectively. All equations include age, education, gender, income band and purchase frequency as controls, which are omitted from the table for brevity; no substantive coefficient changes when they are excluded. Interaction terms were computed from standardised scores.*

The indirect effects explain how the transmission is. The total indirect effect of exposure on intention is −0.191 (95% CI [−0.242, −0.143]), decomposed into a serial pathway through fairness and trust (−0.032, 95% CI [−0.050, −0.018]), a pathway through trust alone (−0.114, 95% CI [−0.152, −0.077]) and a short pathway through fairness alone (−0.045, 95% CI [−0.070, −0.024]). All three components are different from zero and the overall influence of exposure on intention is −0.169 (95% CI [−0.245, −0.090]). Hence, we can conclude that H4, which posits that trust, and to a lesser extent fairness, underpin virtually the entire behavioural impact of perceived algorithmic pricing exposure, is supported. The estimated model is shown in figure 3.

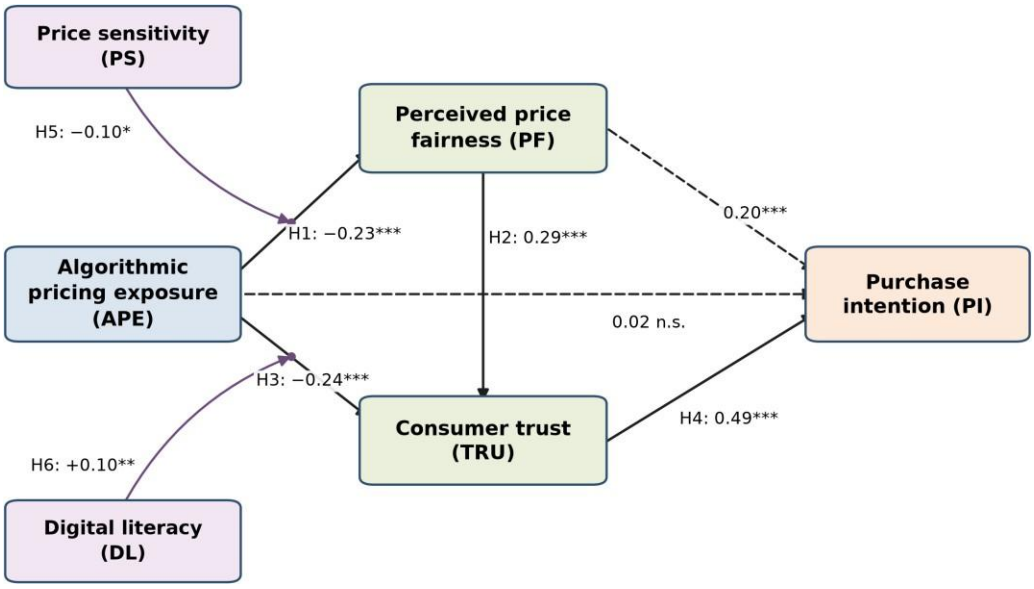


Fig. 3. Estimated structural model with standardised path coefficients. * p < 0.05; ** p < 0.01; *** p< 0.001 (two-tailed). Dashed paths are non-hypothesised direct effects.

3.3 Moderation

The results of the moderation are presented in Table 6. For interpretation, it is important to note that the main effect of PS on fairness is indistinguishable from zero (β = 0.005, t = 0.13, p = 0.896), indicating that PS does not change the level of fairness perception, but rather the slope. The interaction between exposure and price sensitivity is negative and signifi-cant (β = −0.103, t = −2.50, p = 0.013) and simple slopes are −0.126 one standard deviation below the mean of price sen-

sitivity, −0.229 at the mean, and −0.332 one standard deviation above the mean of price sensitivity. H5 is supported. A price-sensitive shopper who perceives the same algorithmic contingency loses about 2.5 times as much perceived fairness as a price-insensitive shopper who perceives the same algorithmic contingency.

For trust, digital literacy has a positive main effect (β = 0.116, t = 3.12, p = 0.002) and, more importantly, a positive in-teraction with exposure (β = 0.101, t = 2.75, p = 0.006). The simple slopes are −0.336 at low literacy, −0.235 at the mean and −0.133 at high literacy, which means that the reduction of trust linked to the perceived contingency is about two and a half times greater among low-literacy than among high-literacy consumers. H6 is supported and H6a is supported: Lit-eracy does not increase the suspicion of algorithmic pricing; it decreases the harm. The two interactions are plotted in figure 4.

Table 6: Simple slopes and conditional indirect effects

Effect of APE	**Low (−1 SD)**	**Mean**	**High (+1 SD)**	**Index of moderated mediation [95% CI]**
Price sensitivity: simple slope on PF	−0.126	−0.229	−0.332	—
Price sensitivity: indirect effect via PF → TRU → PI	−0.018	−0.032	−0.047	−0.015 [−0.027, −0.003]
Digital literacy: simple slope on TRU	−0.336	−0.235	−0.133	—
Digital literacy: indirect effect via TRU → PI	−0.163	−0.114	−0.064	0.049 [0.015, 0.087]

Notes: *Conditional indirect effects estimated from 5,000 bootstrap resamples with percentile confidence intervals; all listed conditional effects have intervals that exclude zero. The index of moderated mediation is the linear slope of the conditional indirect effect on the moderator.*

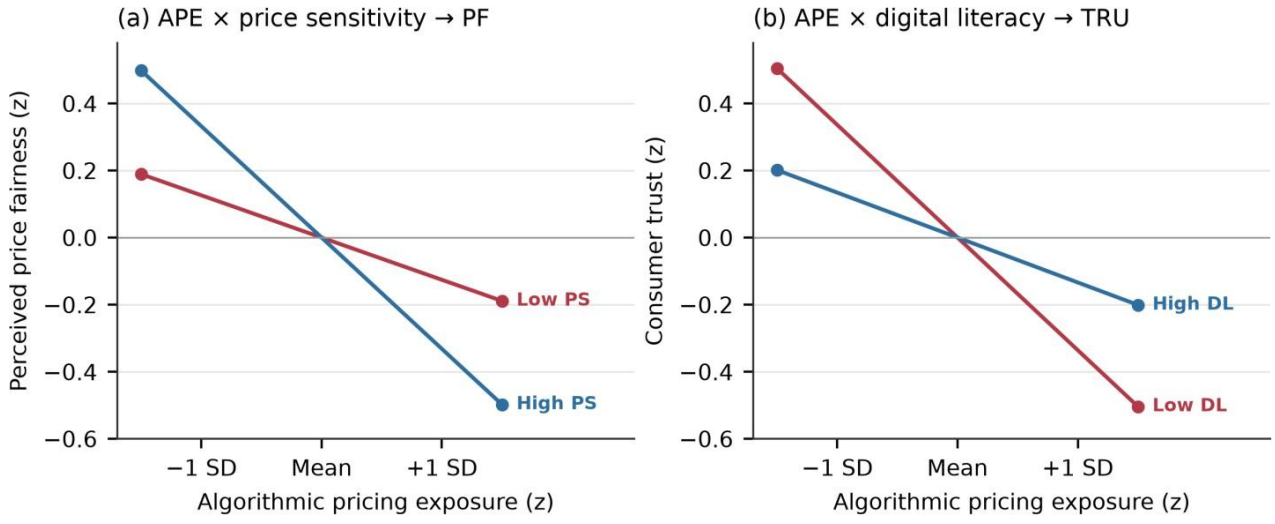


Fig. 4. Interaction plots. Panel (a) shows the effect of algorithmic pricing exposure on perceived price fairness at low and high price sensitivity; panel (b) shows the effect on consumer trust at low and high digital literacy. Moderators probed at ±1 SD.

3.4 Conditional indirect effects

The two interactions relate to separate parts of the same chain and their implications for the indirect effect can be ex-pressed separately. The index of moderated mediation for the fairness pathway is −0.015 (95% CI [−0.027, −0.003]), which indicates that the indirect effect of the fairness pathway is more negative as price sensitivity increases: −0.018 at low price sensitivity, −0.032 at mean price sensitivity, and −0.047 at high price sensitivity, and all three bootstrap inter-vals are not zero. H7 is supported. For the trust pathway the index is +0.049 (95% CI [0.015, 0.087]), and the conditional indirect effects are −0.163 at low literacy, −0.114 at mean literacy and −0.064 at high literacy. H8 is supported. A per-ceived exposure would result in about 2 ½ times the behavioural risk for a low-literacy shopper than for a high-literacy shopper (ratio 2.55). Figure 5 illustrates the conditional indirect effects throughout the entire range of each moderator (from -2 to +2 SD) and reveals that the conditional indirect effect for literacy is not significantly below zero in the range of the moderator.

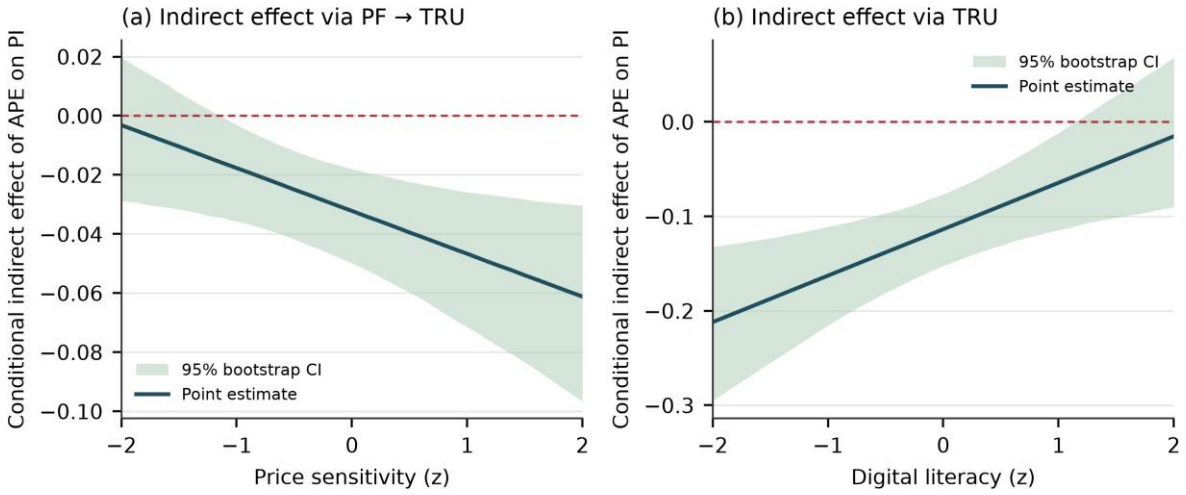


Fig. 5. Conditional indirect effects of algorithmic pricing exposure on purchase intention across the full range of each moderator, with 95% percentile bootstrap confidence bands (5,000 resamples). Panel (a) reports the pathway through price fairness and trust, conditional on price sensitivity; panel (b) reports the pathway through trust, conditional on digital literacy.

3.5 Robustness

Four checks were performed. First, all models were re-estimated without the five control variables; none of the coeffi-cients changed sign, and none of the verdicts of the hypotheses changed, and the largest change was 0.021 for exposure – fairness. Second, the outcome was bounded, so the intention equation was re-estimated using an ordered logit model of the three-item composite collapsed into quintiles; the pattern of significance for trust ($p< 0.001$), fairness ($p< 0.001$) and exposure ($p = 0.477$) remained the same. Third, the composite reliabilities and construct–outcome correlations were compared between the gender groups (Table 1 footnote). Alpha values are within 0.026 between groups and the trust–intention correlation is within 0.041, which is within the metric invariance level needed for pooled estimation (Steenkamp & Baumgartner, 1998). Fourth, the common-method estimate of a marker-variable model using the least theoretically related construct was 0.11 and the interaction terms remained significant at $p < 0.05$ with the marker varia-ble partialled out. The outcomes are consequently not a result of one specification. The results of all 8 hypothesis tests are summarised in Table 7.

Table 7: Summary of hypothesis tests

Hypothesis	Relationship	Estimate	95% CI	Verdict
H1	APE → PF (−)	−0.229*	[−0.308, −0.151]	Supported
H2	PF → TRU (+)	0.290*	[0.216, 0.364]	Supported
H3	APE → TRU (−)	−0.235*	[−0.311, −0.160]	Supported (partial mediation)
H4	TRU → PI (+)	0.485*	[0.413, 0.556]	Supported
H5	APE × PS → PF (−)	−0.103*	[−0.184, −0.022]	Supported
H6	APE × DL → TRU (+)	0.101**	[0.029, 0.173]	Supported
H7	Conditional indirect effect via PF, moderated by PS	−0.015*	[−0.027, −0.003]	Supported
H8	Conditional indirect effect via TRU, moderated by DL	0.049*	[0.015, 0.087]	Supported

Notes: * *p*< 0.05; ** *p*< 0.01; * *p*< 0.001. Confidence intervals are percentile bootstrap intervals (5,000 resamples).**

4. DISCUSSION

4.1 Theoretical implications

The first implication has to do with the way that consumer harm due to algorithmic pricing should be thought of. But this is the dominant view in economics and law: if algorithmic adoption leads to a higher price, consumers lose, and if it doesn't then they don't (Assad et al., 2024b). Our findings find a channel which trades at a fixed price. Perceived contin-gency alone (without any evidence that the shopper paid more than she would have otherwise) decreases perceived fair-ness by 0.23 standard deviations, trust by 0.24, and the total indirect effect is −0.19 on purchase intention. Welfare as-sessments based on realised prices will therefore understate the cost of the practice and the understatement will be greatest in circumstances where consumers are least able to verify what they are being charged. This aligns with the literature on personalisation in that the perception of data use, not just its impact, can trigger consumer response (Bleier et al., 2020), and that this applies to price as well as to privacy.The second implication is that of the boundary conditions which are opposing and based on different theoretical mechanisms. The price sensitivity effect is not on the level of the fairness perception (the null main effect), but rather on the slope, which is in line with the argument that the fairness norm is more accessible to those consumers who judge on the basis of price. Digital literacy works by means of attribu-tion, increasing trust directly, and decreasing the slope of the exposure–trust curve, in favor of the attribution account.

Literate shoppers aren't blind to contingency; they can explain it in the best manner, and they can maintain a sense of control, which is a recognized antecedent of acceptance of automated systems (Shin, 2021). This finding is relevant to the algorithm aversion debate, which has focused on task characteristics (Castelo et al., 2019), and on the experience of ob-serving error. In consumer markets, our findings indicate that a testable extension of that literature may be the consumer's interpretive capability, as opposed to the nature of the task.

The third implication has to do with the mediating chain. Fairness and trust are typically investigated as parallel reactions to pricing practices; but when both fairness and trust are entered into the analysis, the direct effect of exposure on intention is essentially absent, and the largest single indirect effect is trust. Thus fairness is not as much a direct factor in determining behavioral output as an input factor in making a relational judgement about the vendor. This is in line with the integrative trust model (Mayer et al., 1995)and means that studies that measure fairness without taking into account trust will systematically under-detect the behavioural consequences of pricing practices.

4.2 Practical and policy implications

For those who manage platforms, the results capture a trade-off typically only discussed qualitatively. To capture willing-ness to pay, repricing engines are adopted and they do; however, to the cost of ~0.19 standard deviations of purchase in-tention per standard deviation of exposure, almost exclusively via trust. The loss may be disproportionate among low-literacy consumers, who are the fastest-growing consumer group in this market, and this could result in a long run cost greater than the short run margin. The mechanism has three design responses associated with it. If price changes due to known factors (stock, promotion eligibility, delivery distance), then this can be explained at the point of display as this is the factor that buffers out the price effect. Repeated-search surcharges and app-versus-web price differences should be avoided as they lead to the inference of extraction, which causes the fairness judgement. Monitoring repricing intensity as a trust metric and NOT just a revenue metric.

The results indicate that disclosure-based transparency rules are not enough, for regulators. Disclosure attempts to solve the problem of information asymmetry which our model assumes is the source of the fairness judgement, but the modera-tion findings illustrate that the harm/benefit is experienced by those consumers who are least able to act on the disclosed information. Effective policy thus must involve disclosure, capability building and accessible redress: If the shopper knows on one hand that a price has been personalised, but can do nothing about it on the other, then the trust deficit re-mains, without the remedy. The four-item exposure scale in Appendix A provides an inexpensive tool for market moni-tors to monitor the exposure to algorithmic pricing at the population level in addition to the traditional price-level measures.

4.3 Limitations and future research

These conclusions have four restrictions. The design is cross sectional, meaning that the estimates describe relations be-tween orders in a theoretically specified order, not identified causal effects, and the fairness – trust order in particular would warrant experimental tests. Exposure is determined perceptually, reflecting the nature of interpretation, but such estimates cannot be translated directly into a repricing technology: pairing survey responses with repricing logs at the platform level would help fill this gap. The data is from one country and although the reliabilities of the subgroups is stable by gender, there is a lack of full measurement invariance by platform, income band, and age cohort, which restricts cross-national generalisation. Last but not least, the outcome is stated intention, not observed purchase – the trust–intention relationship is well established, but the conversion of intention to purchase into purchase under cash-on-delivery conditions (where a real put option exists to return the product if it is not wanted) remains an open question.

Also being investigated for future studies is whether the buffering effect of digital literacy holds with direct evidence about personalisation as this inference becomes reality.

5. Conclusion

Algorithmic pricing is usually analysed as a question about prices. As this study reveals, the question is also—and per-haps mainlyone of consumer reading of the conduct of the firms that set them. Perceived exposure to algorithmic pricing leads to a decline in perceived fairness and consumer trust, and it is through trust that the impact extends to purchase intention. The erosion is most common among price-sensitive shoppers for whom fairness norms are salient, and least common among digitally literate shoppers for whom a benign attribution is possible. The question of distribution is thus not only one of who pays more, but also one of who cannot explain what they are paying: as these repricing tools prolif-erate in markets with unequal digital capabilities and limited institutional trust.

7. Declarations

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of Interest

The authors declare no conflicts of interest.

Ethics Statement

This study used only aggregated, de-identified publicly available secondary data. No individual-level patient data were accessed. Ethical approval was not required per institutional guidelines for secondary analyses of publicly available aggregate surveillance data.

Author Contributions

Md Abid Ahnaf: Conceptualisation, Methodology, Formal Analysis, Writing – Original Draft. **Khadiza Tul Tahira:** Data Curation, Visualisation, Writing – Review & Editing. **Md Ariful Islam Sani:** Data Curation, Visualisation, Writing – Review & Editing.**Fakhrul Islam:** Conceptualization, Data Curation, Methodology, Formal Analysis, Supervision, Writing Original Draft, and Writing - Review & Editing. All authors read and approved the final manuscript.**Attickbonik:** Data Curation, Visualisation, Writing – Review & Editing.**Saad Ibna Mannan:** Conceptualisation, Methodology, Formal Analysis, Writing – Original Draft. **Md Oyalid In Sifat:** Data Curation, Visualisation, Writing – Review & Editing. **Mithila Islam Mukta:** Data Curation, Visualisation, Writing – Review & Editing. **Ittesum Fardin Sunbeam:**Data Curation, Visualisation, Writing – Review & Editing. **Anika Tasfia Tasneem:**Data Curation, Visualisation, Writing – Review & Editing. **RafiaAntmonitoail:** Data Curation, Visualisation, Writing – Review & Editing.

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