

Data, Prices, and Consumer Choice in Algorithmic Markets

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ABSTRACT

Algorithmic pricing, central to market dynamics, is rapidly changing the nature of consumer-industry relationship and competition strategy. This paper is an exploration of consumer perspectives, attitudes and awareness regarding the use of algorithmic pricing by firms and assess their trust, willingness to pay and general perceptions surrounding ethical concerns with respect to its use. It is aimed at highlighting the consumer perceptions and awareness since algorithmic pricing impacts consumers in ways that are continuously emerging aided by technological advancements. This is a mixed-methods research relying on both quantitative and qualitative methods and using cross-sectional data analysis. It explores the correlations between different variables and suggests existing gaps in awareness and trust factors despite some awareness about algorithmic pricing. Findings suggest that policy gaps exacerbate ethical concerns that widen the awareness gap among consumers.

Keywords: algorithmic pricing, consumer perceptions, data economy, price fairness

1. Introduction

For most people, the key factor that differentiates the products of one firm from those of another is price. As a result of this, pricing decisions are important to firms, as they recognize pricing strategy as a critical lever that simultaneously influences profitability, market share, and competitive positioning (Baye & Prince, 2014). Historically firms have employed static, manually driven pricing mechanisms rooted in cost or competitor based strategies, requiring managers to conduct periodic market research, analyse competitor pricing, forecast demand and set prices that remained largely fixed until explicit strategic decision-making prompted their revision (Nagle & Muller, 2017). However, over the past decade, this paradigm has undergone a fundamental transformation (Chen & Zhang, 2020). The convergence of three critical forces: advances in computational capability, the exponential availability of real-time digital data, and the sophistication of machine learning and artificial intelligence (AI), has enabled firms to

delegate pricing decisions to algorithms, fundamentally reshaping how prices are determined, adjusted, and optimized in the marketplace (Cestianu & Mela 2021).

Algorithmic pricing is the use of automated computer programs and machine learning models to set, adjust, and optimize prices in real time, based on continuously updated data inputs reflecting demand, supply, competitor actions, inventory levels, customer characteristics, and broader market conditions (Chen & Zhang, 2020). Unlike traditional approaches where human judgment sets a price point that persists for weeks or months, algorithmic pricing systems can adjust prices continuously, and is being used across diverse industries. Airlines, hotels, ride-sharing platforms, e-commerce retailers, food delivery services, entertainment venues, and subscription-based businesses all adopt algorithmic pricing to varying degrees.

The drivers of this shift are threefold. First, increase in computational ability, directly increasing storage capacity, allowing much larger volumes of data to be stored. (Brynjolfsson, McAfee, 2017). Second, the proliferation of digital touchpoints, like websites, mobile applications, APIs, and IoT devices, generates unprecedented volumes of real-time data about customer behavior, preferences, and market conditions (Brynjolfsson, McAfee, 2012). Third, advances in machine learning and AI have enabled algorithms to detect patterns that would have been invisible to human managers, and analyse the data available to produce insights that can be used to exploit consumer demand (Cestianu, Mela 2021).

This paper discusses the profound implications of this shift. At the firm level, it increases profits, helps in advanced inventory management and allows quick responses to market changes. However, risks surface in damaged brand perception and possibilities of algorithmic collusion and antitrust violations. On the consumer front, mistrust and rejection is seen as a direct response to such strategies, however the degree of such a reaction has been noted to differ across different variables. The effectiveness of such models in different pricing strategies such as penetration and skimming has also been discussed. The paper attempts to explore threefold questions that emanate from the use of algorithmic pricing, its effects on market competition, consumer perception and scope of ethicality.

Throughout, the paper acknowledges that the natural shift towards more advanced policies creates benefits for both firms and consumers, but also serves to remind readers that these benefits come at a cost. It ends with recommendations and an overall judgement on whether algorithmic pricing is an ethical application of advancing technology.

2. Literature Review:

Algorithmic Pricing is a strategy that firms employ to change or vary their prices in response to analysis of consumer data by an algorithm. This pricing strategy can be of two types: Dynamic

Pricing or Personalized Pricing (Seele, 2019). In dynamic pricing, firms use data such as market conditions, supply, demand or time of the day to establish the most profitable price of products for the consumer. On the other hand, in Personalised pricing, the customer's purchasing behaviour is monitored, and along with other factors, such as gender, age, and geographic location, this data serves as the base for an algorithm to decide the price of a product, for a particular customer. Personalized Pricing leverages the "Willingness-To-Pay" of a customer for maximum profit of the firm. Previous studies have discussed the impact of such a strategy (Seele, 2019; Spann, Bertini, 2024; Haws & Bearden, 2006; Kannan & Kopalle, 2001 et al). These studies provide insights into the complications of what seems like an economically sound mechanism.

Implications for Firms:

Firstly, it has been noted that algorithmic pricing in most cases leads to increase in profits (Seele, 2021 et al). Manipulation of prices depending on a consumer's "Willingness-To-Pay" eradicates consumer surpluses, providing consumers the product at exactly the price they would pay for it, nothing less or more. This makes little difference to the customer, if done without explicit intimation, but provides the firms with a massive increase in profit, by shifting these surpluses to the firms (Seele et al, 2021).

If a cold drink, regularly priced at \$5 was increased to \$10 on a hot day, a certain category of consumers would still buy it, due to desperation, regardless of the fact that the price of the drink might have been increased from the standard \$5. Here, the algorithm detects two things, first, a high temperature record for the day, and two, the willingness of a particular consumer to pay an increased price. The latter may be inferred from purchasing history, website cookies etc. This small increment of \$5 made little difference to the category consumer that was willing to pay more for it, because they were probably more well to do, but it made a big difference for the firm, which pocketed an additional \$5. This level of manipulation on a large scale can lead to skyrocketing profits for firms globally, provided the changes are not detected by the consumers, and their willingness to pay is correctly assessed by the algorithm.

The second argument made in favour of algorithmic pricing at the firm level is improved inventory management (Seele 2021, et al). Since algorithms have the capability to both remotely monitor inventories and influence pricing, they can be used to make optimum use of limited stocks. If a firm is running on low stock, but demand is high, prices can be raised, increasing per-piece profit on the product. On the other hand, if the company is well stocked, or maybe even has dead stock, prices can be lowered to flush out the inventory. This way, pricing can be regulated in tandem with the resources available to the firm, and the firm can operate at their maximum production possibility.

The third argument made in support of such models is that they allow managers and firms to respond more quickly to market changes, such as changes in supply and demand or new regulations in their industries (Ham, He & Zhang 2022). This makes pricing processes much more efficient, and simple for managers. However, the system brings about many problems for firms. The foremost being loss of consumer trust, discussed further in the Consumer section later.

Another problem that arises at the firm level is loss of control. Most managers that avoid algorithmic pricing do so because it involves handing over pricing strategy, a very pivotal aspect of a business to a machine that is extremely complicated and difficult to understand. (Spann et al 2024) Since managers cannot trace the working of these models, they consider it as good as handing over the reins of their business to someone else and opting out of it entirely. This loss of control also has consequences beyond managerial perceptions, such as reduced explainability to consumers (Bertini et al 2024). When managers themselves do not understand how and why their products have been priced a certain way, they find it difficult to explain to inquiring customers, and often do not explain at all. In situations of protests or boycotts, they are left answerless, crumbling their brand image.

Due to these perceived risks, some managers, despite understanding the benefits of algorithmic pricing, stay away from such strategies. They advocate for explainable algorithms, human in the loop mechanisms and clear internal ownership, giving indication as to who owns pricing and who controls its strategy.

Implications for Competition:

Algorithmic pricing also affects markets with respect to competition. General regulations regarding competition, collusion and Anti-trust have not been updated to match the innovation in technology.(Seele 2021 et al) AI systems and algorithms that change prices over periods of time do so through machine learning models. They make decisions and learn whether they should repeat such a decision again depending on the outcome of the said decision. For example, these algorithms learn by setting the price of a product \$5-\$10 above or below normal and then record the changes in sales and behaviour of consumers, based on which they decide whether they need to lower or increase these prices in the future. This learning based model proves risky when algorithms learn to collude (Calvano 2019 et al). Collusion, which is illegal in most countries, happens when firms agree to deliberately synchronise their pricing strategies so as to obtain a particular outcome. This is usually manifested by firms raising their prices together, leaving consumers with no option but to spend more on a product which could have been bought at a much lower price.

Algorithmic pricing amplifies this effect because algorithms learn off past decisions and monitoring of prices of the competition. When competition raises prices, if algorithms also raise prices and learn of increased profitability, the algorithms will repeat this behaviour multiple times (Calvano 2019 et al). This leads to artificial implicit collusion where the algorithm has literally learned to collude because of the benefits it has reported. This is a violation of the intention of most Competition Laws that declare collusion and explicit agreements between firms to fix prices illegal. However, since algorithmic collusion might not be explicit, it is not a blatant violation, and this unfair operation of markets continues as a loophole in the current legislature (Pastorello 2019).

Implications for Consumers:

When talking of consumers, while the general conversation tends to lean in the direction that algorithmic pricing corrodes trust and creates negative impacts, there are varied reactions depending on certain variables. This erosion of trust is taken very emotionally by consumers primarily because of expectations of mutuality in the relationship between consumers and firms.

The most important variable here becomes Consumer-to-Consumer Differences. Consumers react most negatively when they find that another customer has paid lower for the exact same product or service. (Haws, Bearden 2006). This triggers intense feelings of inequality. The consumer feels targeted and wronged by the company. They then begin to antagonise the firm, and distance themselves from purchasing in the future unless absolutely necessary. Violations of these principles of justice elevate reaction beyond general dissatisfaction (Yalcin, Dogan, Gurbuz, 2022). This feeling of inequality and difference from the public creates discomfort. Beyond discomfort, the relational damage caused due to perceived unfairness amplifies the negative emotions of the consumers. Seller based differences are viewed with much less hatred. For example, if the price of the same product varies between two sellers, customers are likely to attribute this to market competition rather than the “seller cheating on them”. (Haws, Bearden 2006).

Drawing from these impacts, it has been concluded that a consumer’s discovery of algorithmic pricing, especially when differing among individuals, erodes trust in the firm (Kannan & Kopalle 2001). This is a factor which is hard to gain back, hence firms lose a very big advantage, that is their consumer base, for a particular period of time. In the world of algorithmic pricing, the technological accuracy of algorithms allows them to change prices within milliseconds. Frequency is extremely high. Finding a larger time interval between price fluctuations is difficult. As a result of this, most consumers notice the instantaneous changes and perceive them as highly unfair. The consumers feel violated and manipulated.

To summarise, levels of consumer hatred as a consequence of algorithmic pricing heavily depends on the prices paid by others around customers, the timeframe of price changes, consumer's control over the mechanisms, the rules of pricing, level of inputs used and sector expectations. However it has been concluded by researchers that price fluctuation beyond a fair cost-based price is perceived as unfair by most people (Jin, Morwitz et al, 2024).

Implications for pricing strategy

Algorithmic pricing also has implications on pricing strategies. The algorithmic models require excessive training to understand and operate differently for different strategies (Jin, Morwitz et al, 2024). If a firm practices penetration strategies, where they keep prices low to gain market share and then gradually increase prices, the models need to be trained to respect the low price positioning and avoid opportunistic hikes as soon as high demand is detected.

The primary purpose of algorithmic pricing is to extract consumer surpluses and shift them to the firms, with profit maximisation being a key priority. However, in strategies like penetration, that aim to build a long term consumer base by capturing market share at low prices, profits might take a dip. Firms usually have to reduce margins and operate low profit for the first few months with such strategies, however the focus of the algorithm unless trained otherwise is high margins and high profits (Spann et al 2024). This difference in interests and goals can hamper the overall pricing mechanism. While firms try to prioritise long term profit, the algorithms are driven by opportunities to pocket profit quickly, on a consumer to consumer level in the present. Hence these models require intense training to pass up on opportunities to earn quick profit by increasing prices, and keep the prices low.

3. Research Questions:

1. What are the implications of algorithmic pricing on firms and market competition?
2. How do consumer fairness perceptions change with the introduction of algorithmic pricing?
3. Is algorithmic pricing ethical?

4. Methodology

The study of algorithmic pricing holds immense significance in a market that is heavily reliant upon technological upgrades. This study adopts a survey-method instrument to capture consumer perceptions and attitudes on algorithmic pricing strategies. This research is exploratory in nature attempting to establish correlations between key variables- trust, privacy concerns, willingness to

pay, algorithmic data usage etc and consumer perceptions. A survey method ensures systematic data collection allowing for a wide range of attitudes, perceptions and preferences to be recorded. Survey questions have been designed to gain insight into the consumer-side of the story and find trends according to demographic groups. The survey also includes open-ended questions to capture qualitative insights into respondents experiences and concerns with respect to algorithmic pricing. These responses help to contextualize and support quantitative findings.

5. Sampling

The sample size for this study consists of 270 respondents drawn using a non-probability sampling method. Respondents were sought through online circulation of a survey using google form. The target sample included individuals across a broad age range (under 18 years to 50 years and above) to understand the difference in consumer behaviour and attitudes, digital familiarity and awareness. Ninety percent of respondents belong to urban agglomerates while a small nine percent to suburban regions. Among the 270 respondents, 148 are male and 122 are female respondents.

Age Group	Percentage of Sample
Under 18	4.8%
18-25	4.8%
26-35	17%
36-50	58.5%
50+	14.8%

Table 1.1: Sample By Age

Data was collected using a structured questionnaire consisting primarily of closed-ended questions with a few follow-up open-ended questions to get experiential narratives. The survey instrument was designed based on existing literature and studies on data pricing, consumer behaviour and market dynamics. The survey was administered online over a fixed period and respondents were recorded anonymously. The survey consists of four sections, demographic details, fairness and brand perception, data usage and transparency and a section that uses situations to test perceptions on various other aspects of algorithm pricing and legal regulations.

Overall, variables that were captured in the survey comprise the following- demographic variables as discussed, consumer perceptions of trust, fairness, ethical acceptability, economic preferences and regulatory attitudes. These were measured using five-point Likert scales and situation-type questions along with open-ended questions to explore respondents' concerns and experiences in their own words.

Data Analysis was conducted using Microsoft Excel and data interpretation with the help of charts generated by google forms. Descriptive statistics, including frequencies and percentages were used to generate trends in responses across perceptions. Data filtering and cross-tabulation was employed to examine associations between different variables and demographic profile. Open-ended responses were reviewed and grouped thematically to contextualise and support the quantitative findings.

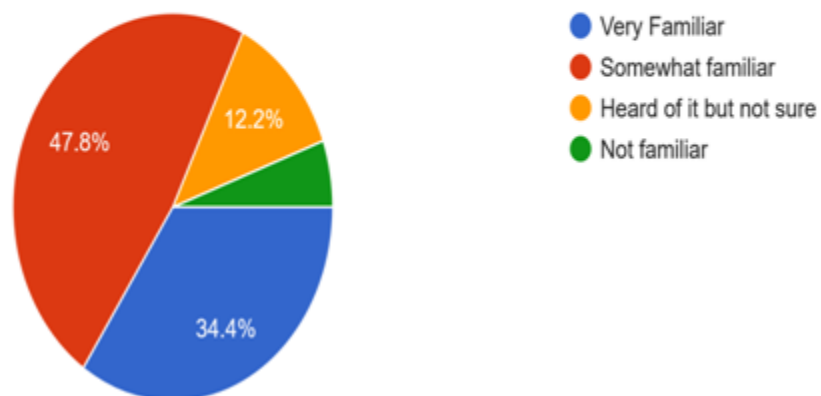
6. Result and Analysis

A key observation made upfront, was that despite 47% of the sample being somewhat familiar, and 34% very familiar with the concept of algorithmic pricing, an overwhelming 52% people were unsure about the laws regarding algorithmic pricing.

Figure 1: Familiarity with Algorithmic Pricing

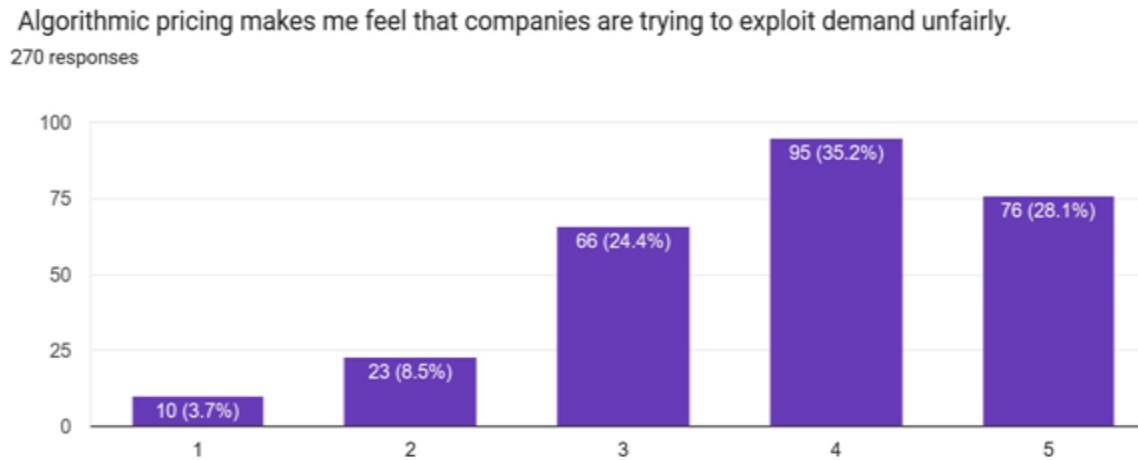
How familiar are you with the concept of algorithmic or dynamic pricing (prices that adjust automatically based on demand, location, or customer data)?

270 responses



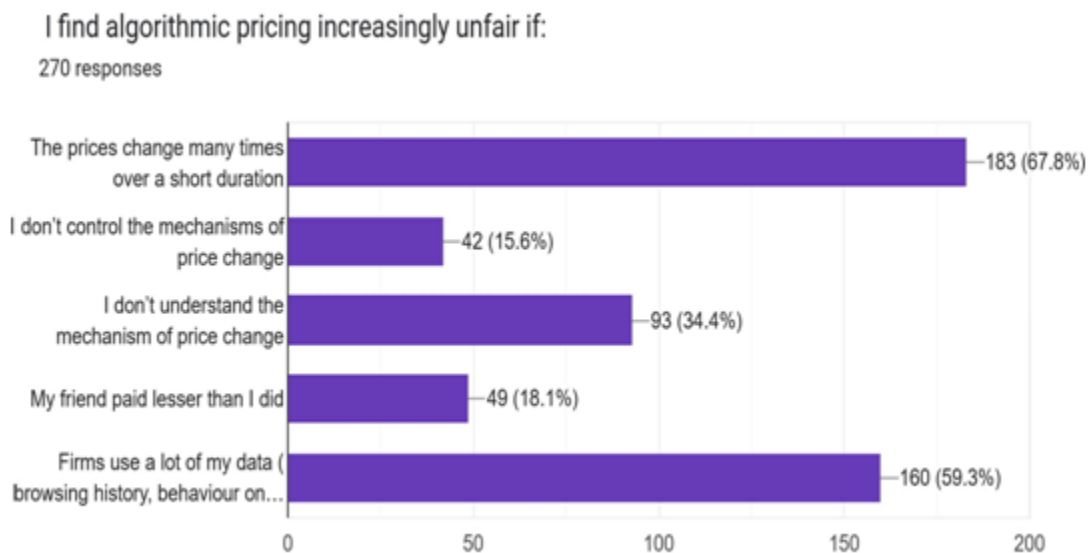
When asked about the correlation between supply-demand and algorithmic pricing, 38% of people disagreed that the two were related, while 30% remained unsure. However, 63% people agreed that algorithmic pricing is exploitative.

Figure 2: Perceptions on demand manipulation by firms 1 is Strongly Disagree and 5 is Strongly Agree



61% report negative feelings when new customers are offered lower prices, a similar 63% feel surge pricing of services during peak hours is unfair, and 71% people find it unfair that customers with higher purchasing power are charged more for products and 67% have expressed disapproval towards high price change frequency. Only 18% of people find algorithmic pricing unfair when their friends pay less than them. However, 59% people agree that firms using a lot of their data makes algorithmic pricing increasingly unfair for them. Not understanding price-change mechanisms is unacceptable to 34% of people.

Figure 3: Fairness perceptions on price change

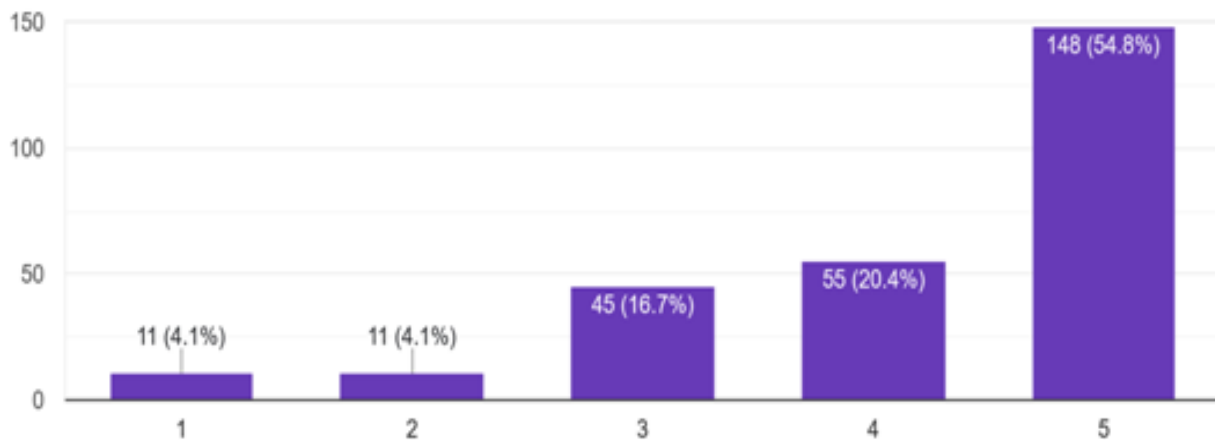


On discovering that a brand uses algorithmic pricing, 67% said that their perceptions would be impacted negatively, with a mere 7% ready to switch brands immediately. 62% of the sample agreed that they would be more comfortable with algorithmic pricing when companies clearly explained how prices were determined, and 69% reported that they would trust the company more, offering a positive change in perception. However, an interesting contradiction is seen as only 36% said that they would be more likely to purchase the product in such a case, with 64% people expressing hesitance towards buying. 48% agreed that they would not use a service if they discovered that the prices were adjusted based on their browsing history, and 25% still expressed willingness to engage in such services. When asked if they would share their data in exchange for discounts and lower prices, 56% surprisingly disagreed, and 46% said that they would pay higher to ensure that their data is not used.

Figure 4: Views on legal regulation

I support legal regulations that limit both price variation and the use of personal data in algorithmic pricing.

270 responses



A unanimous response was seen where 91% of people responded in favour of legal regulations limiting price variations and personal data usage in algorithmic pricing. 36% of the sample thinks that prices should never change once set, and 37% agreed that prices should change once a week, with only 11.5% responding in favour of continuous, real-time adjustments. An overwhelming 63% consider algorithmic pricing fair in the airline industry. Utilities and healthcare reported the least support, at 12% and 9% respectively.

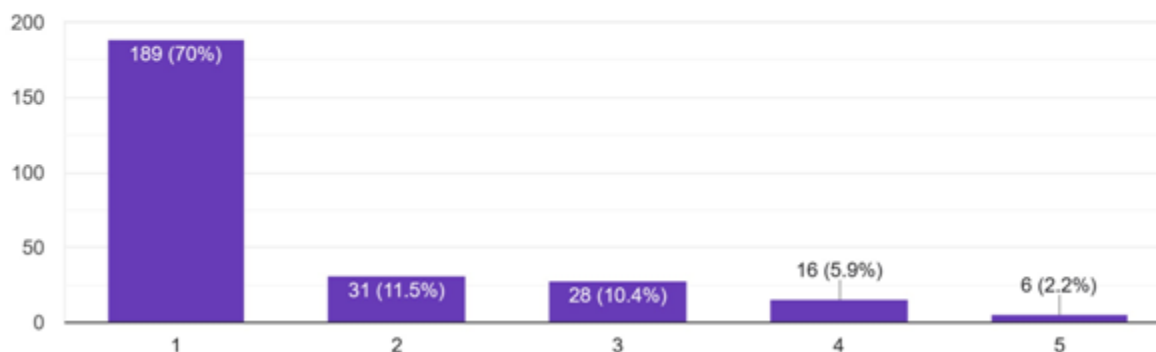
Table 1.2: Sector based fairness perceptions

Sector	Percent that found fair
Airline	63.3%
Hotel	58.1%
Food Delivery	24.4%
Entertainment	22.6%
Utilities	12.6%
Luxury Goods	43.3%
Healthcare	9.6%

Only 43% of the people agreed that algorithmic pricing is ethically unacceptable, while 34% were unsure. When plunged into real world scenarios, such as a real-time price increase while booking a flight, 57% said that they would switch platforms. Responses on utilities such as reaction to an increase in food delivery prices during peak hours remained divided, with 45.2% continuing with the order and 54.8% abandoning it. 57% find city based discrimination extremely unfair whereas 91% find price hikes in healthcare facilities during medical emergencies unfair.

Figure 5: Essential services pricing perceptions

During a natural disaster or pandemic, a pharmacy uses an algorithm that increases prices for high-demand essential goods (masks, hand sanitizer... 300% above normal. How ethical is this practice?
270 responses



The survey included two qualitative questions, one on changes that would make users more comfortable with algorithmic pricing, and the other on personal experiences. Respondents suggested a “Human Override” to assess ethics when technology fails. Many respondents

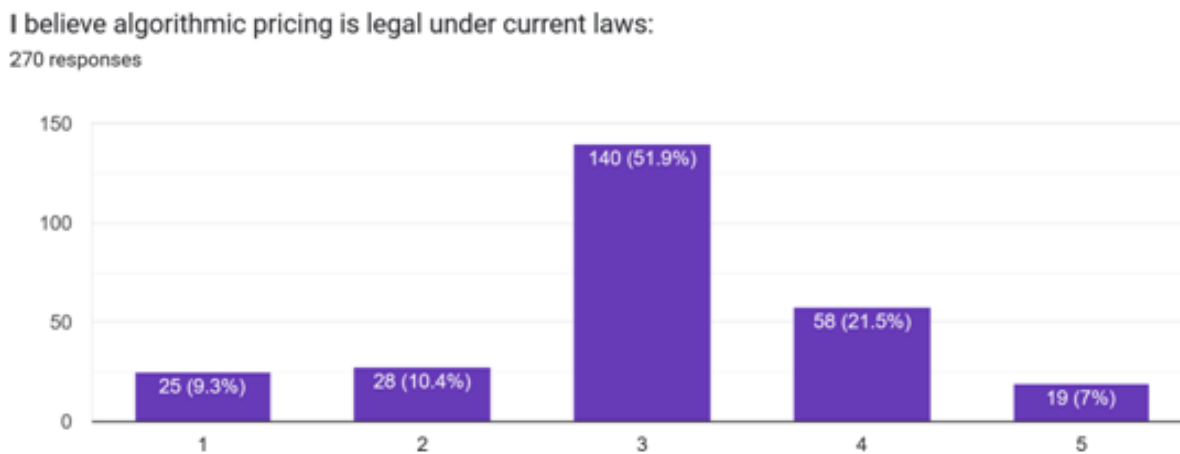
advocated for transparency, with answers like “Telling the customer why the price has increased, providing graphs and trends”. Respondents suggested caps on price fluctuation, and keeping prices reasonable. They expressed acceptance for algorithmic pricing in sectors like air travel, but rejected it in healthcare. They talked about not using personal data. One respondent stated, “(Data) Definitely should not be used to increase prices and get more profit from the customer”.

The respondents were keen on disclosing personal experiences. One stated, “After becoming a regular user, your awards reduce rather than increase”. Another added, “I bought something online and when I checked the next day, it was selling for less.” One user even cited the Indigo Airlines crisis in India, stating, “Indigo cancelled their flights and the other airlines started charging higher, leaving a bitter taste for sad and helpless customers.” A very interesting response actually came from a respondent who had helped their company integrate such a strategy, “I implemented an algorithm which used user(partner) data to reduce the company’s cost of operations. It felt fair till I was sitting at my fancy workplace and working for the company which helped me pay my bills. The bubble burst during the ground check, when I witnessed a 40 year partner see an earning drop of more than 50% as a result of my doing. He was anxious and in unwarranted mental trauma. It shook me to my core.”

7. Discussion

The majority of the sample was aware of algorithmic pricing, and had probably even experienced its effects first hand, yet they seemed unsure in most responses. When asked about the legality of the strategy, responses were restricted to the middle of the 5-point Likert Scale, revealing a massive structural gap in formal awareness of the issue at hand.

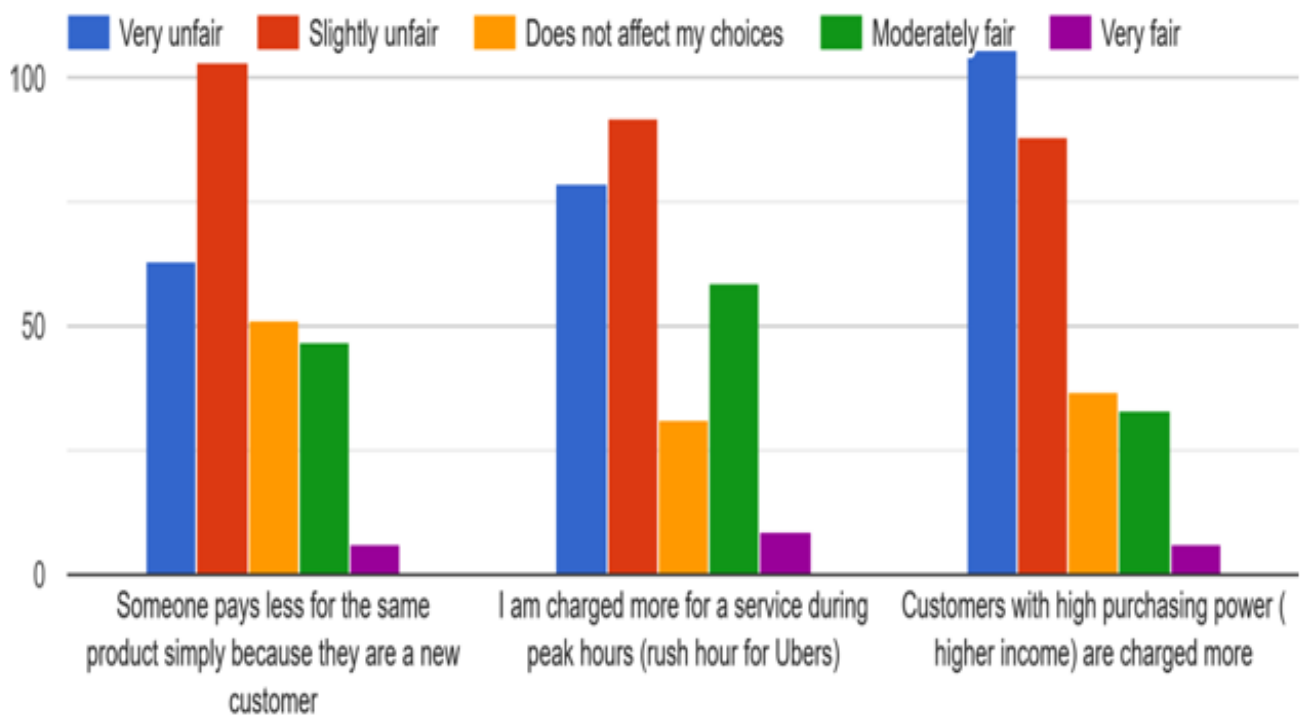
Figure 6: Awareness on Current Legal Status



The sample however unanimously agreed that algorithmic pricing is exploitative in nature. This was evident in the qualitative responses where users spoke of how helpless and disappointed they feel when they save, only to find prices have increased, just because of where their city or phone.

In a diverse sample, from homemakers to students, consensus emerged that charging higher prices to those with greater purchasing power feels unfair. Both low and high income groups prefer uniform pricing across economic backgrounds, highlighting a surprising rejection of classic notions, according to which the lower spectrum would rather have those at the top pay more, and those at the top would be indifferent as it would not affect them much.

Figure 7: Scenario based perceptions

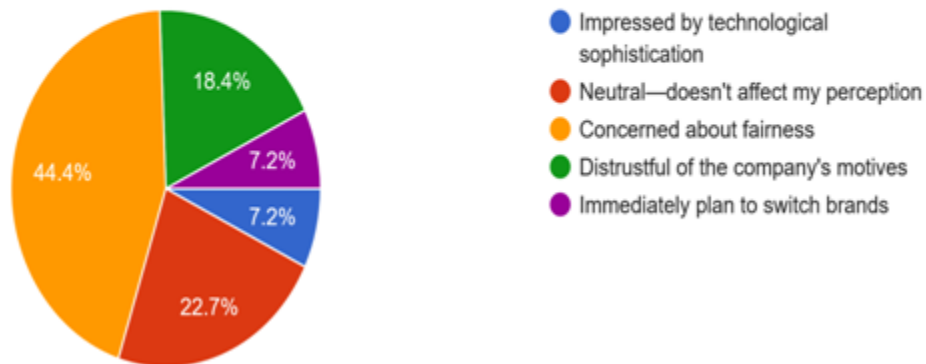


Respondents expressed their dissatisfaction with price discrimination between new and old customers, where new customers are offered lower prices. This reveals that the sample is unhappy with firms' policy of offering more benefits to new customers rather than rewarding old and loyal customers. This also exacerbates the profit-driven mindset most firms operate in. Offering reduced prices reduces Customer Acquisition Costs for companies and warrants higher conversion rates for them, at the expense of loyal customers that are aggravated by such strategies. They feel that their loyalty goes unrewarded and do not see value anymore.

Figure 8: Perception on awareness of algorithm usage by firms

If you discovered that a brand you use a lot has been using algorithmic pricing, how is it most likely to affect your perception of the brand:

270 responses

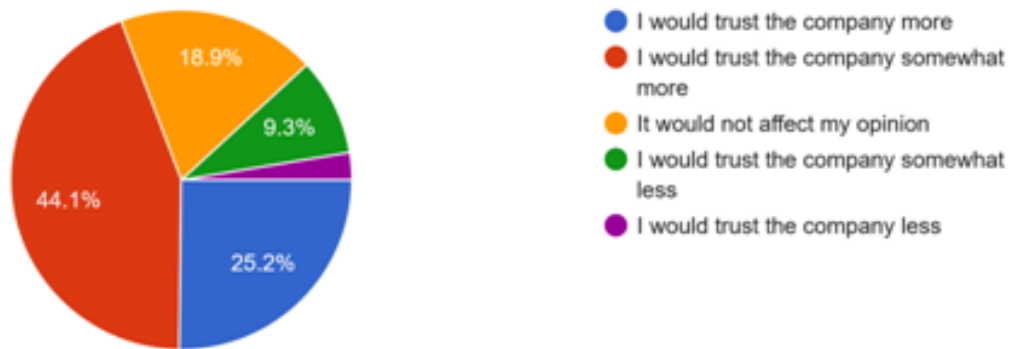


When discussing the impact of data policies on users and how this affects their perception, it has been observed that roughly 67% of the sample has expressed a negative perception shift. This is alarming, since most firms, whether aware or not, continue to use such policies, and risk such a massive negative perception shift. The fragility of the situation can be further understood when customers agree that transparency positively impacts their perception of the firm, through increased trust.

Figure 9: Attitude towards firm transparency

If a company is transparent about using algorithmic pricing, how would it affect your attitude toward the company?

270 responses



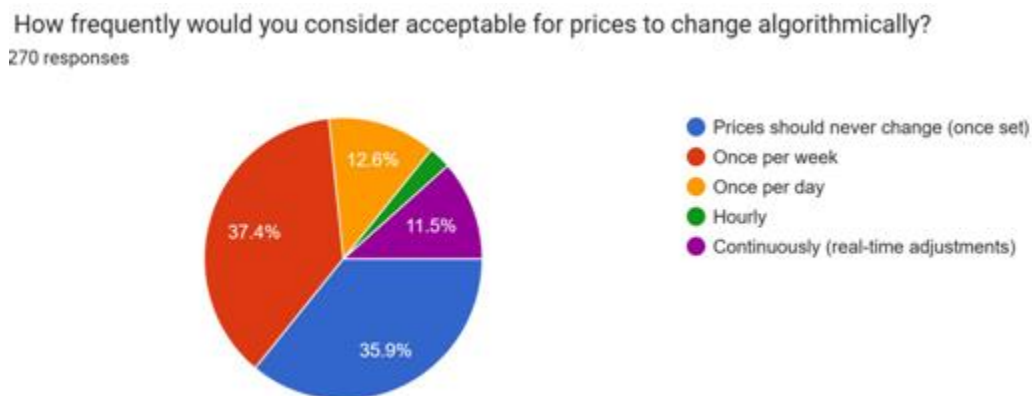
Yet, 64% say that they would hesitate, or not buy products from a firm using algorithmic pricing. This puts firms in a complicated position. Transparency might help their brand image, but it does not necessarily translate to sales. Disclosure of policies does not help the firms financially, hence they must be careful when deciding between perception and sales. Users are sure that they are not likely to buy products when they realise that their browsing history is used. The sample is clear on the fact that they do not wish to exchange their data for discounts and lower prices. They are ready to pay more to ensure that their data is not used. This is an additional revenue stream that firms should explore, after considering its ethical nature.

Figure 10: Price-Data tradeoff



When broken down on a sector basis, users flag the airline and hotel industry as those where algorithmic pricing is fair. A key observation in sector-based application is that there is a resounding consensus against the use of algorithmic pricing in utilities, healthcare and during emergencies. They expect prices to change less than once a week, underscoring the lack of understanding of the volatility of market forces.

Figure 11: Acceptable price change frequency



The sample supports legal regulations limiting degree of price variation and the use of data in algorithmic pricing. Users also disapprove of surge pricing policies, but to a lesser extent. This reveals that awareness does play a role. When a customer can anticipate that the price of a product or service will rise, they can find a way around it, and the effect is not so profound, justifying the lower disapproval rates. Price frequency is seen to be increasingly unfair to users.

Responders further suggested human overrides to combat such a problem. This is a solution worth exploring for firms, as it addresses a key ethical concern in a way that increases consumer trust.

It becomes abundantly clear how consumer perceptions are impacted. This happens in the following way, as gathered from the responses of the sample:

1. Consumers do not associate market forces like supply and demand with algorithmic pricing, rather they feel exploited, vulnerable and helpless.
2. They are embittered when new customers pay less and feel that their loyalty towards a brand is not rewarded. They are charged more than someone who is not loyal to the brand. This damages brand perceptions and reduces customer bases drastically.
3. Surge pricing during peak hours, while perceived as unfair, is somewhat understandable, as users are aware of these patterns and can thus plan around it. Predictability is a big deal for users, as one clearly stated, "With airlines, I accept fare fluctuations more easily because they're expected and visible over time, but it's unsettling to see prices increase within minutes of repeated searches, which creates a sense of being penalized for interest"
4. The sample does not find it fair that customers with higher purchasing power are charged more, which is fair, considering someone should not be punished for accruing wealth. However, the flip side to this argument stands, that if a privileged person can afford to pay more for a certain product, it seems fair that they do so in the interest of the markets.
5. High frequency of price changes, lack of knowledge of how prices were set and the use of personal browsing data also damages perceptions as is viewed as unfair by the majority of the sample.
6. Users report higher trust levels on disclosure of algorithmic pricing, but still hesitate to buy products from these firms. This reveals that transparency improves perceptions, but is likely to reduce sales, putting firms in a compromising position when deciding whether to disclose their pricing strategies.

7. Algorithmic pricing is perceived as more fair in industries like airlines and hotels, but is least expected on a general basis, with most users expecting prices to stay constant all the time, leaving little room for dynamic market forces.
8. Most users perceive algorithmic pricing in utilities and healthcare as unfair, yet continue to place orders on food delivery apps during peak hour price hikes due to helplessness and lack of an option.
9. The qualitative responses also reveal how consumers feel that algorithmic pricing is a one-sided affair, exploiting demand by leveraging user's data, and using it against them.

It creates a tech-driven society, where profits are valued more than empathy, as firms see emergencies as opportunities to earn more, rather than setbacks where consumers struggle for basic necessities.

This opinion further emphasizes views regarding ethics. Consumers view algorithmic pricing as unethical because algorithms lack situational understanding and prioritize profit over welfare, eroding integrity. It enables unjustified price discrimination via data like browsing history and location, charging different prices for identical products. Vulnerable groups, including less wealthy ones, are inferred as desperate and thus forced to pay more, like ProPublica's 2015 finding that Princeton Review's algorithm used ZIP Code analysis to overcharge Asian families 1.8x for test preparation.

One respondent summed up the concept in these words, "For a system to be fair and ethical it must be a win-win for both parties. Just increasing prices doesn't help. I buy a product at a price only if I feel worth the value. After all, who wants a cynic who knows the price of everything and the value of nothing." Another correctly added, "Overall, dynamic pricing feels acceptable when it's predictable and linked to real demand, and uncomfortable when it feels opaque, reactive, or exploitative."

8. Conclusion

This paper set out to understand algorithmic pricing, and its implications on firms, consumers & market competition, and finally to analyse whether it was ethical or not. To a great extent, these goals have been achieved, with comprehensive findings, tying consumer perceptions to impact of algorithmic pricing on firms, and its implications. Consumers find algorithmic pricing exploitative, and report fairness concerns on discovery of its usage. However, transparency plays a big role, where consumers express increased trust in brands who themselves disclose their policies, yet, this heightened trust does not translate to purchase and monetary value, putting firms in a compromising position, with an interesting tradeoff between perceptions and sales. A

few consumers were able to appreciate the strategy, praising it for its demand regulation mechanisms, labelling higher prices as a function of increased demand, rather than exploitation. However, consumers still find algorithmic pricing in utilities and healthcare unacceptable, and are currently unaware of legal regulations in the area.

Firms stand to benefit from algorithmic pricing, as consumer surpluses are redistributed to them, leading to increased profits. It also helps with inventory management and regulation through improved demand management. Firms can respond to market volatilities faster with algorithmic pricing. Two problems arise from the firm end; first, loss of consumer trust, which drastically reduces sales; and second, loss of managerial control, where human elements lose control of pricing mechanisms to technology and thus find it difficult to explain and justify its decisions, a core aspect of customer welfare.

Market Competition also changes, as algorithms programmed for implementing measures to earn maximum profit tend to collude with other algorithms and companies, overstepping the legal boundaries of pricing strategies. Algorithms coordinate price rises and drops with competition prices, leading to implicit collusion, or price-fixing, violating Anti-Trust principles.

Algorithmic pricing is generally labelled unethical due to its inconsiderate nature. Algorithms, trained on facts, numbers and data, are incapable of situational awareness, and this leads to multiple controversies in pricing strategy. A firm might benefit a lot from increasing the prices of medical supplies during pandemics, but this exacerbates the struggle of innocent consumers for no fault of their own. Further, it leverages user data against them, to analyse and commoditise their vulnerabilities. For example, a consumer who has visited a brand's website multiple times is assessed to have a higher Willingness-To-Pay, and the price of products for this user are automatically increased. Furthermore, differentiation and so called "personalisation" is also done through location, age and demographic data. This essentially violates consumer privacy to their disadvantage, earning the "unethical" label.

Algorithmic Pricing is still a new concept to most consumers, who have undeniably faced its consequences without realising. Awareness is required, so that consumers can take an active part in a firm's decision to use algorithmic pricing, giving them the importance they require as a key stakeholder in any financial transaction. This paper confirms past research underscoring the increasingly negative perception shifts of consumers who are victim to such policies, and urges firms to examine alternative strategies. Firms must also introspect, weigh the advantages and disadvantages, before implementing such risky structural changes.

Gaps still exist in the sea of our knowledge of algorithmic pricing. Its exact impact on marginalised groups is unknown. The use of data by the algorithms is not fully understood.

Researchers should look into the variables used to profile a user, and how such information is collected without violating the user's privacy. Is this information general supply-demand data, or is it personal data like browsing history and social media activity? A clear distinction should be made between the two branches. Secondly, who should be held accountable if the algorithm makes a discriminatory decision. At the current stage, there is a fundamental lack of a structured procedure when it comes to failure of algorithms. Thirdly, surge pricing and price hikes on utilities should be explored and the ethical nature of such strategies should also be comprehensively analysed on a large scale, listing detailed impacts for firms and consumers. Lastly, there exists a profound gap in consistent international regulation of algorithmic pricing, and data policies at large. Such laws are mainly regional and lack uniformity, making it confusing and inconclusive. Research should be aimed at understanding these diverse regulations and recommending a consolidated approach forward.

This paper also provides certain policy recommendations, with transparency being the cornerstone of future regulation. Governments should mandate transparency measures, where companies should be required to disclose either pricing history, in the form of charts, graphs and trends, or factors which determine the price a consumer sees. Either of these allow consumers room for planning to avoid surged prices. Secondly, companies should have human overrides in place to account for instances when technology fails to assess with humanity. Such measures would look like routine checks by managers, or a simple Human-In-The-Loop mechanism where a human approval is required before major changes. This ensures accountability and consumer welfare, aspects profit-driven algorithms are unable to incorporate. Furthermore, in order to curb tacit algorithmic collusion, a technological workaround should be designed, such that the weight of competition pricing in the algorithm's decision is either reduced or removed entirely. This would prevent coordinated pricing that leads to implicit collusion. Data Collection & Usage Laws should also be updated to incorporate the advent of Algorithmic Pricing. Clear regulations should be established regarding the usage of data that a firm collects from an individual. Passive monitoring of browsing or search history should be limited, if not banned. Data routes must be strictly regulated to avoid violations of consumer privacy. Lastly, a uniform international standard for the use of data in pricing should be established.

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