

REVIEW

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Digital Pricing Management in Online Business Models: A Systematic Review of Dynamic Pricing, Customer Fairness, and Revenue Optimization

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Abstract

Digital pricing has become a central managerial capability in online business models, where firms increasingly move beyond fixed prices toward dynamic, algorithmic, and personalised pricing systems. This shift reflects the growing availability of behavioural data, competitive intelligence, platform analytics, and machine learning tools that allow prices to be adjusted more frequently and precisely. However, the same capabilities that support revenue optimization also intensify concerns about fairness, transparency, and customer trust. This systematic review examines how digital pricing management has been studied across pricing strategy, revenue management, consumer psychology, retailing, tourism, platform economics, and algorithmic governance. The review focuses on three connected themes: dynamic pricing and revenue optimization, customer fairness and trust perceptions, and managerial control of automated pricing practices. The aim is to clarify what is known, where evidence remains fragmented, and how future research can integrate performance and governance perspectives. Following a PRISMA-informed approach, the review synthesises peer-reviewed journal articles published between 2010 and 2025. The selected evidence includes conceptual, empirical, modelling, experimental, and review-based contributions relevant to digital pricing in online and data-rich business environments. The review does not introduce new empirical data but systematically collates and interprets existing research. The review concludes that digital pricing management should be understood as both a revenue optimization system and a trust-sensitive managerial practice. Firms need pricing architectures that combine analytical precision with transparency, accountability, and human oversight. Future research should develop integrated models that examine profitability, fairness, governance, and long-term customer relationships together rather than as separate research streams.

Keywords Algorithmic pricing, Systematic review, Digital pricing, Dynamic pricing, Revenue optimization, Customer fairness

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Introduction

Digital pricing management has transformed pricing from a periodic managerial decision into a continuous, data-enabled capability embedded in online business models. Dynamic pricing in digital markets allows firms to update prices in response to demand, competition, inventory,

customer behaviour, and platform conditions, while broader digital pricing systems increasingly rely on algorithmic learning and automated decision support [1]. This development is especially visible in travel, hospitality, retail, and platform markets, where revenue management and price optimization have become central to value capture [2].

As a result, pricing is no longer only a marketing-mix instrument but also a core digital business model mechanism.

The strategic appeal of digital pricing lies in its capacity to increase revenue quality by matching prices more closely to market conditions and willingness to pay. Evidence from tourism and hospitality shows that dynamic price variability can support revenue maximization when firms manage demand fluctuations and capacity constraints effectively [3]. Online hotel pricing studies further demonstrate that digital channels provide conditions under which firms can observe demand patterns and adjust prices in near real time [4]. Yet these advantages depend on modelling quality, competitive context, and customer acceptance rather than on automation alone.

The central problem addressed in this review is that revenue optimization can conflict with customer perceptions of fairness, trust, and transparency. Research on personalised dynamic pricing shows that consumers may react negatively when they believe prices are tailored in ways that exploit individual vulnerability or information asymmetry [5]. Studies of online personalised pricing also indicate that mandated disclosure can alter purchase intentions, suggesting that transparency is not simply a regulatory issue but a behavioural determinant of customer response [6]. Therefore, digital pricing must be analysed as a socio-technical practice rather than merely as a computational optimization problem.

This systematic review asks how digital pricing management has been conceptualised, how dynamic pricing contributes to revenue optimization, how customers evaluate fairness and trust, and how managers can govern automated pricing practices. These questions connect the revenue management literature on demand learning and optimization with the consumer psychology literature on fairness and the emerging governance literature on algorithmic pricing [7]. The review is structured around method, pricing management approaches, dynamic pricing evidence, fairness perceptions, governance concerns, research gaps, and future directions. By synthesising these streams, it aims to provide an integrated foundation for research on profitable and trustworthy digital pricing.

Review Method and Selection Criteria

The review followed a systematic review logic informed by PRISMA 2020, which emphasises transparent identification, screening, eligibility assessment, and reporting of included studies [8]. Because digital pricing management spans marketing, revenue management, operations, tourism, retailing, economics, and business ethics, the search strategy was designed to capture both performance-oriented and fairness-oriented research. The review included peer-reviewed journal articles published from 2017 to 2026 that addressed dynamic pricing, algorithmic pricing, personalised pricing, revenue optimization, price fairness, customer trust, or governance of automated pricing practices. The resulting corpus was treated as a systematic synthesis of existing evidence rather than as a meta-analysis because the included studies used heterogeneous theories, methods, industries, and outcome measures.

The search process prioritised Q1 and field-leading outlets relevant to digital marketing, pricing strategy, revenue management, retailing, management science, business ethics, and consumer behaviour. Search terms combined concepts such as digital pricing management, dynamic pricing, revenue optimization, algorithmic pricing, personalised pricing, customer fairness, trust, governance, discrimination, and collusion. Articles were eligible when they directly examined digital or data-enabled pricing practices, developed models relevant to dynamic pricing decisions, tested customer responses to pricing variation, or addressed managerial and ethical control of algorithmic pricing [9]. Articles were excluded when they were not peer-reviewed journal publications, did not concern pricing in online or data-rich business environments, or focused on unrelated forms of price regulation without implications for digital pricing management.

The screening process evaluated relevance at the title, abstract, and full-text levels, with particular attention to whether each study contributed to at least one of the review's three themes. Revenue-focused studies were retained when they examined dynamic pricing mechanisms, demand learning, online competition, reinforcement learning, revenue management systems, or price optimization performance [10]. Customer-focused studies were retained when they analysed fairness perceptions, trust, perceived ethicality, transparency, retaliation, complaints, or behavioural responses to digital and personalised pricing [11]. Governance-focused studies were retained when they addressed algorithmic pricing

risks, collusion, discrimination, pricing ethics, legal implications, or managerial oversight [12].

The final sample contained 35 peer-reviewed journal articles published between 2017 and 2026, covering empirical studies, modelling papers, conceptual reviews, systematic reviews, experiments, and governance analyses. **Table 1** summarises the systematic review search strategy, inclusion/exclusion criteria, and final sample. The sample was then coded thematically according to pricing approach, enabling technology, strategic objective, performance evidence, customer fairness mechanism, governance risk, and research gap. This coding allowed the review to compare studies that would otherwise remain separated across revenue management, consumer psychology, platform economics, and algorithmic ethics [13].

Table 1. Systematic Review Search Strategy and Study Selection: Databases, Keywords, Screening Process, and Final Sample Characteristics

Review element	Specification used in the systematic review	Rationale for inclusion in the review design
Review type	Systematic review of peer-reviewed journal articles published from 2017 to 2026	The time window captures recent developments in digital pricing, algorithmic pricing, AI-enabled pricing, and fairness debates
Core search concepts	Digital pricing management; dynamic pricing; algorithmic pricing; personalised pricing; revenue optimization; price fairness; customer trust; pricing governance	These concepts reflect the review's three analytical themes: revenue optimization, fairness perception, and managerial control
Target publication outlets	Marketing, retailing, management science, revenue management, tourism, business ethics, law and	Digital pricing evidence is distributed across multiple fields rather than concentrated in one journal domain

	economics, and service research journals	
Inclusion criteria	Peer-reviewed journal articles; 2017–2026 publication date; direct relevance to online, digital, dynamic, personalised, or algorithmic pricing; contribution to performance, fairness, or governance	These criteria ensured that the evidence base was contemporary, scholarly, and aligned with the research aim
Exclusion criteria	Books, theses, reports, websites, conference papers, non-peer-reviewed sources, and articles without a clear pricing-management focus	These exclusions protected the review from non-comparable or weakly relevant evidence
Screening logic	Title and abstract screening followed by full-text relevance assessment	This staged approach supported transparent narrowing from broad search terms to the final article set
Final sample	35 peer-reviewed journal articles	The final set provided sufficient breadth to synthesise revenue optimization, customer fairness, and governance perspectives
Synthesis approach	Thematic synthesis rather than statistical meta-analysis	Heterogeneous methods and outcomes made narrative and thematic synthesis more appropriate than pooled effect estimation

Digital Pricing Management

Digital pricing management refers to the managerial design and control of pricing systems that use digital data, analytics, and automation to set or adjust prices in online business models. The literature distinguishes dynamic pricing, personalised pricing, algorithmic pricing, and revenue management, although these categories frequently overlap in practice [14]. Dynamic pricing adjusts prices over time or across market conditions, while personalised pricing adjusts prices across customers or customer segments. Algorithmic pricing describes the computational infrastructure through which pricing decisions are automated, learned, or adapted.

The technologies enabling digital pricing include real-time analytics, demand forecasting, machine learning, reinforcement learning, online clustering, competitive monitoring, and platform data integration. Reinforcement learning has been applied to airline revenue management, where algorithms learn pricing policies under uncertain demand and capacity conditions [10]. Context-based dynamic pricing with online clustering shows how firms can update price decisions by grouping demand situations or customer contexts as information arrives [15]. These approaches illustrate that digital pricing management is increasingly shaped by learning systems rather than static pricing rules.

Digital pricing also varies by strategic objective, ranging from revenue maximization to demand smoothing, capacity utilization, customer acquisition, retention, segmentation, and competitive positioning. In service and travel contexts, dynamic pricing has been used to respond to seasonal and temporal demand shifting, as shown in alpine skiing and hotel settings [16]. In online retail and platform contexts, pricing systems may also respond to competitor prices, customer reviews, search behaviour, and reputational signals [17]. The strategic objective therefore determines whether pricing automation is used primarily to extract value, manage capacity, stimulate demand, or protect customer relationships.

A systematic classification of digital pricing management must connect pricing forms with enabling technologies and managerial objectives. **Table 2** classifies digital pricing management approaches and their underlying technologies. This classification shows that dynamic pricing, personalised pricing, algorithmic pricing, and revenue management are not interchangeable categories

but related components of a broader digital pricing architecture [18]. For managers, the challenge is to align technology, pricing logic, customer transparency, and organizational accountability before automation scales pricing decisions across online markets.

Table 2. Digital Pricing Management Approaches: Types, Enabling Technologies, and Strategic Objectives

Digital pricing approach	Core pricing logic	Enabling technologies	Main strategic objectives
Dynamic pricing	Prices vary over time according to demand, supply, capacity, inventory, or market conditions	Demand forecasting, real-time analytics, revenue management systems, machine learning	Revenue maximization, capacity utilization, demand smoothing, margin improvement
Personalised pricing	Prices vary across customers or segments based on inferred willingness to pay or behavioural data	Customer analytics, behavioural profiling, segmentation models, recommendation systems	Value extraction, conversion improvement, segment profitability
Algorithmic pricing	Pricing decisions are generated or supported by automated computational systems	Pricing algorithms, reinforcement learning, competitive monitoring, AI decision systems	Fast decision making, adaptive pricing, competitive responsiveness
Surge pricing	Prices increase during demand peaks, scarcity, congestion,	Real-time demand sensing, platform analytics, capacity monitoring	Balance demand, supply management, scarce resource protection, service availability

	or capacity pressure		
Auction-based pricing	Prices emerge through bidding, matching, or platform-mediated allocation	Marketplace algorithms, bidding engines, platform rules, transaction data	Efficient allocation, marketplace monetization, participant incentives
Revenue management pricing	Prices are optimized across capacity, timing, demand classes, and booking conditions	Forecasting models, inventory controls, optimization algorithms, booking curves	Revenue optimization under capacity constraints
Review-sensitive pricing	Prices respond to online reviews, ratings, and reputation signals	Text analytics, review monitoring, demand learning, reputation analytics	Capturing reputation value, adding to quality signals, managing conversion
Governance-oriented pricing	Pricing systems include oversight, fairness checks, and compliance mechanisms	Human-in-the-loop controls, audit trails, fairness dashboards, disclosure mechanisms	Balance profitability, trust, legal, and accounting

can observe market signals more frequently, which makes demand learning and continuous optimization more feasible than in traditional fixed-price environments. However, the evidence also indicates that dynamic pricing creates value only when algorithms are calibrated to industry conditions, customer expectations, and competitive constraints.

The performance logic of dynamic pricing is especially visible in capacity-constrained industries such as airlines, hotels, tourism, and services. Airline revenue management research demonstrates how reinforcement learning can support pricing decisions when demand is uncertain and inventory is perishable [10]. Field evidence from airline pricing also shows that competition shapes the revenue impact of fare decisions, because pricing changes occur in markets where rival responses and customer search behaviour matter [19]. Similarly, hotel and tourism studies show that dynamic price variability can improve revenue outcomes when demand patterns are sufficiently observable and when price changes are aligned with booking timing and market conditions [3].

Recent modelling studies extend dynamic pricing beyond classical revenue management by integrating online learning, reference effects, customer reviews, clustering, and contextual information. Demand learning with reference effects shows that current pricing decisions may shape future customer expectations, so short-term revenue gains can have longer-term behavioural consequences [20]. Online learning models for revenue management with add-on discounts further demonstrate that pricing performance depends on the interaction between base prices, add-on incentives, and customer purchase decisions [21]. Studies of review-sensitive pricing also show that online reputation can become an input into pricing strategy, linking customer-generated information to revenue optimization [17].

Dynamic Pricing and Revenue Optimization

Dynamic pricing contributes to revenue optimization by allowing firms to revise prices in response to demand uncertainty, competitive movement, inventory constraints, and customer behaviour. Revenue management research shows that pricing performance depends not only on the ability to change prices but also on the quality of forecasting, segmentation, and capacity allocation embedded in the pricing system [7]. In online settings, firms

The evidence suggests that dynamic pricing is most effective when pricing mechanisms, data inputs, algorithms, and managerial objectives are aligned. **Table 3** synthesises the evidence on dynamic pricing strategies and their revenue impacts. The table highlights that revenue optimization is not a single technique but a family of mechanisms that includes demand learning, competitive pricing, reinforcement learning, review-responsive pricing, and context-based clustering [22]. It also shows that the same pricing system may produce different outcomes depending on market transparency, customer

heterogeneity, competitor behaviour, and governance constraints.

Table 3. Dynamic Pricing and Revenue Optimization: Mechanisms, Algorithms, and Empirical Performance Evidence

Dynamic pricing mechanism	Algorithmic or analytical basis	Evidence base in the reviewed literature	Main revenue related contribution
Demand-learning dynamic pricing	Bayesian learning, online learning, adaptive estimation	Demand learning and reference-effect models in management science	Improves price adaptation under uncertain demand
Reinforcement-learning pricing	Trial-and-error policy learning, reward optimization	Airline and competitive pricing studies using reinforcement learning	Supports sequential pricing decisions under uncertainty and competitive environment
Capacity-based revenue management	Forecasting, inventory control, booking curves, price optimization	Airline, hotel, tourism, and service revenue management studies	Enhances revenue with capacity fixed or perishable
Competition-responsive pricing	Competitor monitoring, strategic interaction models, algorithmic reaction functions	Studies on pricing algorithms, competition, and field experiments	Improves responsiveness to rival prices and market movements
Context-based dynamic pricing	Online clustering, contextual learning, customer or	Contextual pricing and online clustering research	Enables price adaptation across changing customer

	situation grouping		demand contexts
Review-sensitive dynamic pricing	Review analytics, reputation signals, demand response models	Studies connecting online reviews and pricing	Allows firms to price according to reputation and perceived quality
Add-on and bundle-related pricing	Online optimization, purchase-sequence learning	Revenue management models with add-on discounts	Optimizes revenue across core and supplementary purchases
Demand-shifting pricing	Temporal demand modelling, seasonal forecasting	Tourism and leisure pricing studies	Moves demand across time periods and increases utilization

Customer Fairness and Trust Perceptions

Customer fairness perceptions are central to digital pricing because online customers can compare prices, share experiences, and interpret price variation as either legitimate market responsiveness or unfair discrimination. Studies of online dynamic pricing and perceived ethicality show that consumers do not evaluate price changes only by economic outcomes but also by perceived motives, transparency, and procedural justice [11]. When customers believe that firms use data asymmetries to charge them more than others, pricing becomes a trust problem rather than a neutral optimization problem. This is especially important in online markets where customers may not understand how prices are calculated.

Personalised dynamic pricing is particularly sensitive because it can blur the line between customer relevance and customer exploitation. Research on personalised prices shows that consumers' fairness perceptions decline when they infer that a special price is based on hidden profiling rather than legitimate segmentation [5]. Airline passengers' reactions to personalised dynamic pricing

similarly suggest that customers may resist prices that appear individually targeted without clear justification [23]. These findings imply that customer acceptance depends on whether digital pricing is framed as beneficial customization, transparent demand management, or opaque extraction.

Fairness perceptions also shape behavioural outcomes such as purchase intention, loyalty, retaliation, complaints, and negative word of mouth. In online retailing, trust can intensify customer backlash when loyal consumers perceive price unfairness, because disappointed expectations may produce stronger retaliation than weak prior relationships [24]. Service research further shows that confusion and unfairness perceptions can increase consumers' intentions to spread negative word of mouth about dynamic pricing [25]. Therefore, customer trust is not merely a buffer against pricing dissatisfaction; it can also heighten perceived betrayal when digital pricing violates relational expectations.

Transparency, consistency, disclosure, and perceived control moderate customer responses to digital pricing. Table 4 summarises the fairness factors influencing customer responses to digital pricing. Evidence on mandated discriminatory-pricing disclosure indicates that disclosure framing can affect purchase intention, which means transparency mechanisms must be designed carefully rather than treated as simple compliance messages [6]. More broadly, fairness-sensitive digital pricing requires firms to explain why prices vary, avoid unjustified discrimination, and maintain customer confidence that pricing systems are not exploiting private information [26].

Table 4. Customer Fairness and Trust Perceptions in Digital Pricing: Antecedents, Moderators, and Behavioural Outcomes

Fairness-related factor	How it affects customer interpretation	Moderating conditions	Behavioural outcomes identified in the literature
Price transparency	Clear explanations make price variation more	Disclosure framing, timing, customer literacy,	Higher acceptance when explanations are credible

	understandable and legitimate	channel design	lower trust when explanation appear manipulative
Perceived discrimination	Customers react negatively when they believe different prices are based on unfair personal profiling	Sensitivity of customer data, prior trust, comparison visibility	Reduced purchase intention, anger, distrust, retaliation
Procedural fairness	Customers assess whether the pricing process appears consistent and justifiable	Rule clarity, consistency across customers, perceived firm motive	Increased acceptance when pricing rules are seen as legitimate
Trust in the seller	Trust shapes whether customers interpret price changes as legitimate or exploitative	Relationship history, brand reputation, loyalty, prior satisfaction	Trust can reduce uncertainty but can also increase backlash if expectations are violated
Customer confusion	Unclear price changes can produce uncertainty and suspicion	Price complexity, frequency of change, competing offers	Complaints, negative word of mouth, low satisfaction
Perceived control	Customers respond better when they can influence price outcomes through timing, choice, or membership rules	Availability of alternatives, flexibility, opt-in mechanisms	Greater acceptance of dynamic pricing when customers see a path to better prices

Reference price expectations	Customers compare current prices with remembered or expected prices	Prior exposure, price history, frequency of changes	Perceived unfairness when price exceed acceptable reference levels
Social comparison	Customers compare their price with prices paid by others	Visibility of price differences, social sharing, platform transparency	Perception of inequity, anger, reduced repurchase intention

Managerial Control of Pricing Practices

Managerial control of digital pricing practices is necessary because algorithmic pricing can produce outcomes that are profitable in the short term but legally, ethically, or reputationally risky. Artificial intelligence and algorithmic decision-making in personalised pricing raise concerns about privacy, discrimination, transparency, accountability, and consumer protection [18]. These risks become more serious when pricing systems operate at scale and managers cannot easily interpret why particular prices were generated. Therefore, digital pricing governance must include not only technical model validation but also ethical review, escalation rules, and accountability structures.

Algorithmic collusion is one of the most debated governance risks in automated pricing. Economic and legal analyses show that AI pricing systems may facilitate coordinated outcomes even without explicit human agreement, particularly when algorithms repeatedly observe and respond to competitor prices [12]. Experimental and modelling evidence on algorithmic pricing and collusion further demonstrates that autonomous pricing agents can learn supra-competitive pricing patterns under certain market conditions [9]. This creates a managerial responsibility to monitor not only firm-level revenue outcomes but also market-level pricing behaviour.

Competition in pricing algorithms also complicates managerial control because firms may design algorithms to respond aggressively, defensively, or adaptively to rivals.

Studies of algorithmic competition show that pricing outcomes can differ substantially depending on algorithmic design, market structure, and the information available to competitors [27]. Dynamic pricing under competition using reinforcement learning similarly suggests that automated systems can generate pricing strategies that are difficult to predict without structured oversight [22]. Managers therefore need governance systems that test algorithmic behaviour before deployment and monitor it continuously after implementation.

The governance challenge extends beyond legal compliance to include organizational reputation, consumer trust, and strategic legitimacy. Ethical reviews of dynamic and personalised pricing argue that algorithmic pricing should be evaluated according to fairness, autonomy, transparency, and social acceptability, not just profitability [13]. Work on the ethics of dynamic pricing similarly emphasises that digital pricing can become problematic when firms exploit behavioural vulnerability, information asymmetry, or customer dependence [28]. Effective managerial control therefore requires human-in-the-loop pricing governance, documented decision rules, audit trails, and clear responsibility for pricing outcomes.

Research Gaps and Governance Implications

The first major research gap is the limited integration between revenue optimization studies and customer fairness studies. Revenue management models often evaluate pricing performance through revenue, demand response, inventory utilization, or competitive positioning, while consumer studies examine fairness, trust, dissatisfaction, or retaliation [7]. These streams rarely model profitability and trust as jointly endogenous outcomes, even though digital pricing decisions can simultaneously increase revenue and damage customer relationships. Future research should therefore examine how pricing algorithms affect both short-term margins and long-term customer equity.

A second gap concerns industry and context coverage, because much of the evidence is concentrated in airlines, hotels, tourism, online retailing, and platform services. Dynamic pricing in resort hotels and tourism demonstrates strong relevance for capacity-based settings, but these contexts do not fully represent subscription platforms, digital marketplaces, software-as-a-service, B2B platforms,

or data-enabled service ecosystems [4]. Consumer fairness studies also often focus on individual customers, leaving organizational buyers and multi-stakeholder procurement environments underexplored. This gap limits the generalizability of digital pricing theory across online business models.

A third gap involves governance design, because many studies identify risks but fewer specify how managers should operationalize oversight. Reviews of artificial intelligence and dynamic pricing call attention to algorithmic capabilities, but governance frameworks remain less developed than optimization models [29]. Research on algorithmic pricing, discrimination, and collusion clarifies legal and economic risks, yet practical mechanisms for auditability, accountability, and fairness testing remain fragmented [12]. This suggests a need for research that translates ethical concerns into managerial routines, dashboards, escalation systems, and compliance protocols.

The final gap concerns the lack of integrated research questions that connect data, algorithms, customers, managers, and regulators. Table 5 maps research gaps to governance implications and future research questions. The table shows that digital pricing governance should not be added after algorithm deployment but built into pricing architecture from the beginning [30]. This is especially important as utility fairness, contextual dynamic pricing, and algorithmic trust become more central to pricing strategy in online business models [31].

Table 5. Research Gaps in Digital Pricing Management: Thematic Deficits, Governance Challenges, and Proposed Research Directions

Research gap	Why the gap matters	Governance implication	Proposed future research questions
Separation between revenue optimization and fairness research	Profitability and customer trust are often studied independently even though both are affected by the same	Pricing dashboards should track revenue, fairness complaints, trust indicators, and churn together	How firm optimization reveals what maintains perceived fairness long-term
			How digital pricing norms align with fairness norms across B2B platforms and subscription contexts
			How digital pricing norms align with fairness norms across B2B platforms and subscription contexts
Limited evidence outside consumer-facing travel and retail contexts			Findings from airlines, hotels, and online retail may not generalize to platforms, subscriptions, B2B markets, or digital services
			Governance frameworks should be adapted to industry structure and buyer type
			How digital pricing norms align with fairness norms across B2B platforms and subscription contexts
Underdeveloped human oversight models			Automated pricing can produce harmful outcomes before managers understand their causes
			Firms need human-in-the-loop approval, exception review, and escalation thresholds
			What factors of managerial oversight reduce pricing efficiency with algorithmic decisions
Weak integration of legal, ethical, and managerial perspectives			Collusion, discrimination, and transparency are often treated as separate problems
			Pricing governance should combine legal compliance, ethical evaluation, and strategic risk management
			How firms design pricing governance systems that satisfy regulatory, customer, and revenue goals
Lack of cross-cultural fairness research			Customer tolerance for dynamic or personalised pricing may vary across markets and institutional contexts
			Multinational firms need locally sensitive pricing communication and disclosure practices
			How cultural norms shape acceptance of dynamic and personalized pricing
Insufficient research on algorithmic explainability in pricing			Customers and managers may reject prices that
			Pricing systems require explainable decision logs
			What levers explain improvement in trust when revealing

	cannot be explained	and customer-facing rationale mechanisms	commercial sensitivity, pricing logic
Limited longitudinal evidence	Short-term experiments may miss trust erosion, churn, or reputational damage over time	Managers should monitor long-term customer outcomes after pricing changes	How dynamic pricing practices affect customer loyalty, brand over multiple purchase cycle
Emerging fairness-aware optimization models	Technical fairness constraints are still weakly connected to managerial pricing practice	Firms should evaluate fairness metrics alongside revenue metrics before deployment	How utility fairness revenue optimization can be jointly embedded in digital pricing systems

Figure 1 presents an integrated systematic review framework showing how digital pricing management links revenue optimization, customer fairness perceptions, and governance control in online business models.

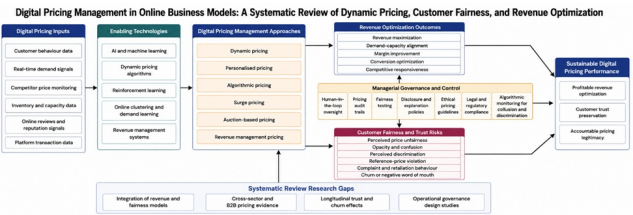


Figure 1. Integrated Systematic Review Framework for Digital Pricing Management in Online Business Models: Linking Dynamic Pricing, Customer Fairness, Revenue Optimization, and Governance Control

Future Research Directions

Future research should develop integrated models that treat digital pricing as a joint optimization and governance problem. Current work on utility fairness in contextual dynamic pricing points toward models that incorporate

fairness constraints into demand learning rather than treating fairness as an external reputational issue [32]. This direction should be expanded to include trust, customer lifetime value, churn, complaint behaviour, and regulatory risk. A stronger research agenda would ask not only which price maximizes revenue but also which price remains explainable, acceptable, and sustainable.

A second direction is to study digital pricing through real-time experimentation while accounting for behavioural and ethical effects. Dynamic pricing research has made important progress in online learning and clustering, but experimentation should also measure perceived fairness, confusion, trust, and repurchase intention [15]. Studies of algorithmic pricing and consumer trust suggest that price search and customer interpretation are shaped by how algorithms are perceived, not only by the prices they produce [31]. Future studies should therefore combine field experiments, platform data, surveys, and behavioural measures.

A third direction is governance design research that examines how firms can manage automated pricing systems in practice. Ethical and legal studies of personalised pricing highlight the need for oversight, but managers still lack clear evidence on how to design audit routines, disclosure policies, human review processes, and escalation thresholds [18]. Research should compare governance configurations across industries and assess whether human oversight improves fairness, reduces reputational risk, or prevents harmful algorithmic outcomes. Such studies would help move the literature from identifying risks to evaluating control mechanisms.

A fourth direction concerns the dark sides of algorithmic pricing, including collusion, discrimination, customer retaliation, and erosion of market trust. Evidence on algorithms of unfairness and personalised pricing shows that customers and observers increasingly question whether data-driven price discrimination is fair or socially acceptable [32]. At the same time, research on competition in pricing algorithms and artificial intelligence collusion indicates that automated pricing may create market-level harms beyond individual customer dissatisfaction [27]. Future research should therefore connect micro-level fairness, firm-level governance, and macro-level market consequences.

Conclusion

This systematic review shows that digital pricing management is a double-edged capability in online business models. Dynamic pricing, personalised pricing, and algorithmic revenue management can improve responsiveness, demand alignment, and revenue optimization. However, these same practices can undermine trust when customers perceive price variation as opaque, discriminatory, confusing, or exploitative.

The review also shows that the digital pricing literature remains fragmented across performance modelling, consumer fairness research, and governance analysis. Revenue optimization studies provide sophisticated tools for adaptive pricing, while fairness studies explain why customers may resist or punish digital pricing practices. Governance research adds a necessary warning that automated pricing can create ethical, legal, and reputational risks if firms rely on algorithms without accountable oversight.

The central implication is that digital pricing should not be managed as a purely technical revenue function. Managers need pricing systems that combine analytical capability with fairness safeguards, transparent communication, human oversight, and long-term customer relationship thinking.

Future research should build integrated frameworks that explain how firms can pursue revenue optimization while preserving customer trust and market legitimacy.

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