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Review

A Systematic Literature Review on Pricing Strategies in the Sharing Economy

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Abstract: As an emerging business model, the sharing economy has gained a large amount of academic attention; the pricing problem in the sharing economy has also been widely investigated. Aiming to capture the current state-of-the-art research on pricing strategies in the sharing economy and foreseeing directions for future research, this article conducts a systematic literature review and content analysis of 158 articles from the Scopus and Web of Science databases. As a result, first, this review proposes an extended definition covering B2C and C2C models and a model structure covering the entire supply chain, based on which 158 articles are categorized into nine sub-models covering 30 scenarios. Second, the general characteristics (i.e., research fields, time and journal distributions, research themes and scenarios) and technical details (i.e., theories, methodologies, approaches, models, and conclusions) of the 158 articles are reviewed and summarized by the pricing party, business mode, and scenario. Finally, this review proposes some future research directions of existing scenarios from the perspectives of information asymmetry, market competition, and empirical approaches, and discusses some extensions, including uninvestigated scenarios and COVID-19-related topics; correspondingly, this review suggests some analytical models and empirical approaches that can be employed to fill these gaps. The proposed research directions and corresponding approaches can be references for future research.

Keywords: sharing economy; price; pricing; systematic literature review

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1. Introduction

Based on the innovation of information communication technologies [1], the sharing economy (SE) enables individuals to reciprocally share their underutilized assets or service capacity through online peer-to-peer (P2P) platforms. Due to its price advantage [2], SE has rapidly developed into a phenomenal business model with diverse practices since the emergence of representatives, such as Airbnb, Uber, and BlaBlaCar, operating worldwide [3]. SE has become a complex framework covering numerous scenarios.

The business success of SE has attracted a large amount of academic attention, and a vast amount of research on SE has been conducted. Meanwhile, in the development of SE, price acts as an essential factor that smooths the sharing transaction process by signaling the quality of shared products [4], the complexity of crowdsourcing tasks [5], and the condition of the sharing market [6]; therefore, how the price is decided in SE (i.e., pricing strategies in SE) has been widely investigated. Meanwhile, the existing literature reviews have systematically reviewed research on definitions, frameworks, and practices of SE (see Appendix A Table A1), while research on pricing strategies in SE has only been roughly [7–10] or fragmentally [11,12] reviewed. Therefore, to fill this review gap, and more importantly, to obtain comprehensive knowledge of the current state-of-the-art research on pricing strategies in SE, and find research gaps for further research, this article conducts a systematic literature review and content analysis of 158 articles from the Scopus and Web of Science databases.

This systematic literature review is organized as follows. In Section 2, an extended definition covering both C2C and B2C models and a model structure including the entire

supply chain are proposed, which jointly provide a two-dimensional classification for diverse sharing scenarios, namely, the business model dimension (i.e., B2C and C2C models) and the pricing party dimension (i.e., manufacturer pricing, firm pricing, provider pricing, intermediary pricing, and requester pricing). In Section 3, following the PRISMA protocol, the search process is implemented in the Scopus and Web of Science databases; after identification, screening, eligibility, and inclusion, 158 articles are finally identified. In Section 4, according to the proposed classification, 158 articles are grouped into nine sub-models covering 30 scenarios; a systematic literature review and content analysis are then conducted by the pricing party, business model, and scenario. As a result, the general characteristics (e.g., research fields, time and journal distributions, research themes and scenarios) and technical details (e.g., theories, methodologies, approaches, models, and conclusions) of the 158 articles are reviewed and summarized. In Section 5, future research directions of existing scenarios are proposed from the perspectives of information asymmetry, market competition, and empirical approaches, and extensions including uninvestigated scenarios and COVID-19-related topics are discussed; correspondingly, analytical models (i.e., signaling game, cheap talk, auction, reverse auction, and mechanism design) and empirical approaches (i.e., SEM, DCM, DID, RDD, Chow Test, SUEST, and Fisher's Permutation Test) are suggested to fill these gaps. Additionally, the limitations of this review are discussed. In the final section, the main findings and suggestions are concluded.

2. Background

SE is an umbrella concept that covers a variety of terms (e.g., sharing economy, collaborative consumption, P2P consumption, and access-based consumption) [13]. Schlagwein, Schoder [14] proposed three key features of SE, namely, IT-facilitated, peer-to-peer, and no transfer of ownership. However, these features are no longer compatible with emerging sharing forms, such as the encroachment of professional agents [15] and business firms (e.g., Mobike). Therefore, to obtain a more comprehensive understanding of SE and clarify the boundary of SE, the definition of SE is extended as follows.

The sharing economy is an IT-facilitated consumer-to-consumer (C2C) or business-to-consumer (B2C) model for the commercial or non-commercial sharing of underutilized goods or service capacity through an intermediary without transfer of ownership.

Meanwhile, considering the entire supply chain [16], the model structure of the extended definition is illustrated in Figure 1. It should be mentioned that, in the extended definition, the B2C and C2C models differ depending on the providers in the sharing market, that is, in the B2C model, providers are business firms, while in the C2C model, providers are individuals.

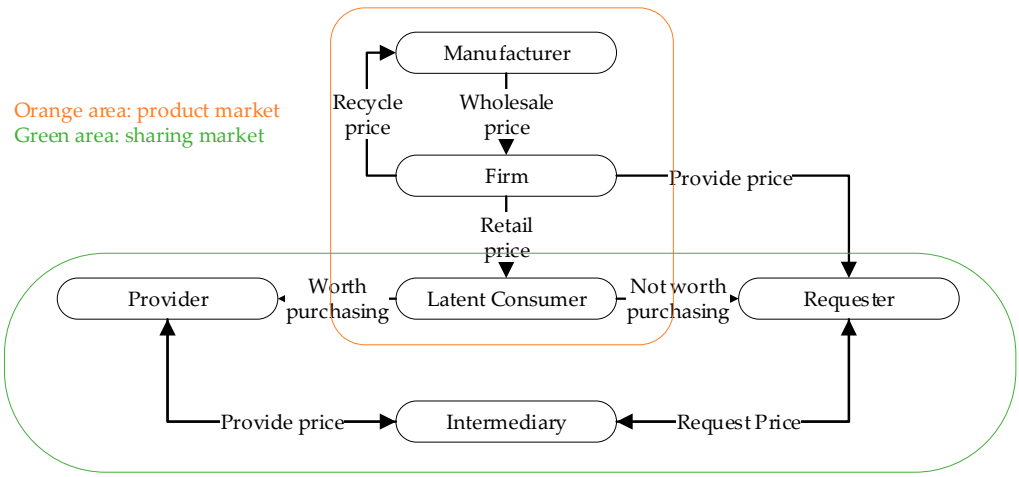

Figure 1. The extended sharing economy model structure.

As illustrated in Figure 1, the product market (orange area) consists of the manufacturer, firm, and latent consumer. The manufacturer produces products, sells them to the firm at a wholesale price, and recycles damaged products from the firm at a recycling price [17]. Then, the firm sells the products to latent consumers, who will purchase products if their perceived values are higher than the retail price (i.e., worth purchasing), or otherwise, they will not purchase them (i.e., not worth purchasing) [16]. After the purchase decision, latent consumers leave the product market and join the sharing market.

The sharing market (green area) consists of the provider, requester, and intermediary. Purchasing consumers join the sharing market and share their products when vacant; therefore, they become providers in the sharing market. Non-purchasing consumers come to the sharing market to rent products from providers; therefore, they become requesters in the sharing market. Apart from individual providers (i.e., C2C model), the firm can also encroach on the sharing market by directly providing a rental service to non-purchasing consumers (i.e., B2C model). Transactions between providers and requesters are reached through an intermediary (e.g., online platform), wherein requesters pay the request price to the intermediary, and the intermediary pays the provide price (or the sharing price) to providers and charges a commission fee. It is noteworthy that in the sharing market, not only physical or virtual products, but also services, such as production capacity and labor, can be shared (e.g., gig economy, crowdfunding, crowdsourcing, and ride hailing).

3. Methodology

In the existing literature reviews, the systematic literature review (SLR) is widely adopted. SLR is an approach to synthesize a large volume of research and conclude research progress and gaps, jointly with the preferred reporting items for systematic reviews and meta-analysis (PRISMA) protocols [18], which offer clearer and less biased guidance of the review process [13,19]. This review's PRISMA protocol is illustrated in Figure 2.

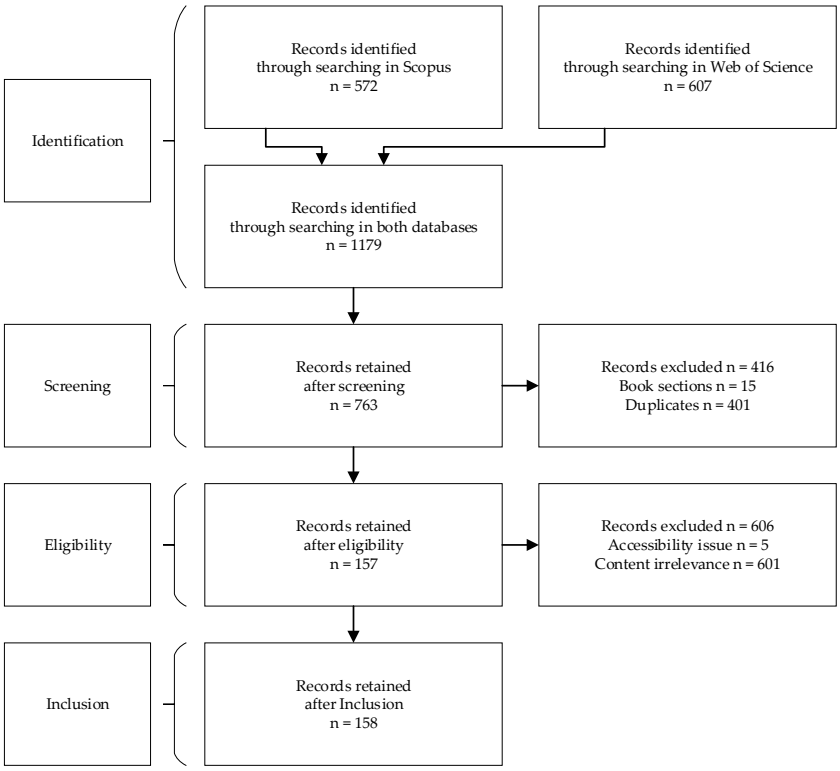

Figure 2. Flowchart of the PRISMA protocol.

A standard PRISMA protocol includes four stages: identification, screening, eligibility, and inclusion. In the identification stage, this review searches relevant English journal articles of all periods in the Scopus and Web of Science (WOS) databases, which cover most journals [20]. Search terms are listed by block [13] in Table 1.

Table 1. Final search terms of pricing in SE.

Block	Search Term
Dependent Variable	Price or pricing AND
Context	"sharing economy", "collaborative consumption", "peer-to-peer consumption", "p2p consumption", or "access-based consumption" [13], "peer-to-peer accommodation" or "p2p accommodation" [11], "commercial sharing system" or "access economy" or "peer-to-peer market" or "P2P market" or "gig economy" or "piecemeal labor" or "do-it-yourself economy" or "diy economy" or "platform economy" or "crowd-based capitalism" or "on-demand economy" or "peer-to-peer economy" or "p2p economy" or "mesh economy" or "rental economy" or "community-based economy" or "commons-based peer production" [21], "bike sharing" or "bicycle sharing" [22], "ride sharing", "ride hailing", or "ride sourcing" [12], "car sharing" [21], "vehicle sharing", "crowdsourcing" [23], "crowdfunding" [24], "collaborative fashion consumption" [25], "sharing platform", "peer-to-peer platform", or "p2p platform" [21]

In Scopus, the search scope includes the title, abstract, and keyword, and in WOS, the search scope includes the title, abstract, keyword, and keyword plus. To ensure reliability and quality, conference papers, book chapters, reviews, and so on, are excluded [26]. After conducting the search on 31 December 2020, 572 articles from Scopus and 607 articles from WOS were identified for further stages.

At the screening stage, articles not published in peer-reviewed journals (e.g., conference paper, working paper, or book chapter) and duplicates were excluded due to concerns of reliability and quality [13]. After screening, 15 book sections and 401 duplicates were excluded, and 763 articles were identified for further stages.

At the eligibility stage, articles were viewed by title, abstract, keyword, and full text to assess the relevance to this review's theme. As a result, five articles were excluded for no access, 606 articles were excluded for content irrelevance, and 157 articles were identified for the final stage.

At the inclusion stage, the references of the 157 articles were checked to see if any of the literature had been missed. As a result, one article published in Marketing Science in 2011 was included.

In summary, 158 articles were finally identified and coded for content analysis. Due to the space limitation, the coding results were summarized into Supplementary Materials and uploaded to the journal's website for download, and the findings are presented in the following section.

4. Findings

4.1. General Characteristics of Existing Research

As illustrated in Figure 3, the first study on pricing strategies in SE was published in 2011, while 106 identified articles (67.1%) were published in 2019 and 2020. Furthermore, 86 journals covering management science, marketing, hospitality and tourism, transportation, economics, sustainability, computer science, and so on, were identified. Figure 4 lists 13 journals with at least three identified articles published, in which 73 published articles were identified in total (46.2%). Additionally, seven articles were published in the UTD 24 Leading Business Journals. The remainders were published in journals well-recognized in related fields (e.g., *Journal of Economic Theory* and *Navel Research Logistics*).

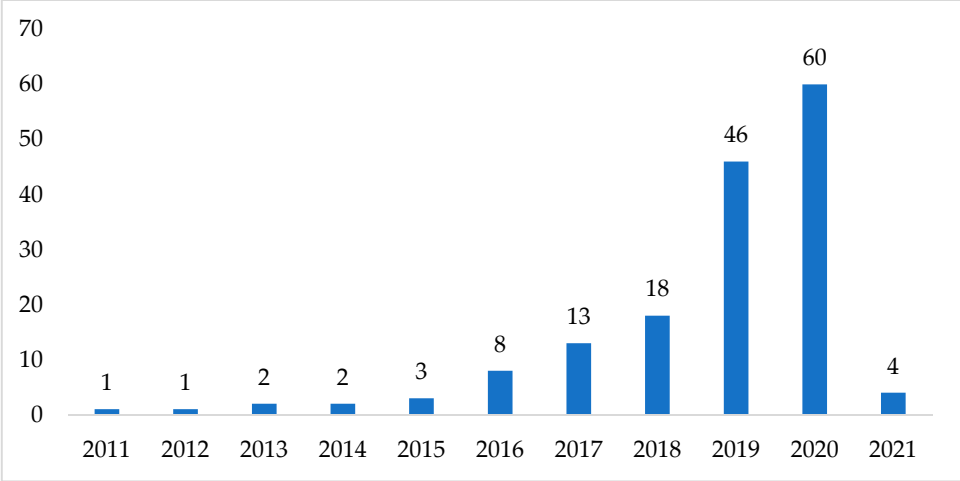

Figure 3. Volume of published articles by year.

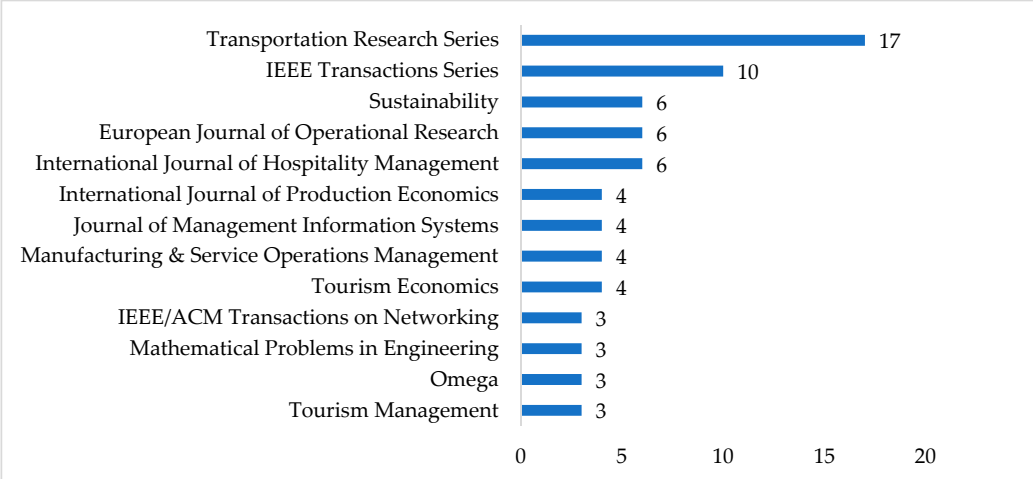

Figure 4. Volume of published articles by journal.

According to the proposed classification in Section 2, 158 identified articles were classified into nine sub-models covering 30 scenarios (see Table 2). In general, 106 identified articles (67.1%) investigated C2C sharing, and 59 articles (37.3%) investigated B2C sharing. Specifically, 48 C2C articles (45.3%) investigated provider pricing (mostly P2P accommodation), 45 C2C articles (42.5%) investigated intermediary pricing (mostly ride hailing), 36 B2C articles (61.0%) investigated provider pricing (mostly crowdfunding), and 19 B2C articles (32.2%) investigated requester pricing (mostly crowdsourcing).

Table 2. Identified themes by business model and pricing party.

Business Model	Pricing Party	Theme	Reference	Count	Total
B2C	Manufacturer	General model	[17]	1	1 (0.6%)
	Firm	General model	[27–29]	3	4 (2.5%)
		Information Sharing	[30]	1	
	Provider	General model	[17,27,31]	3	36 (22.8%)
		WIFI sharing	[32]	1	
		Bike sharing	[33–38]	6	
		Vehicle sharing	[39–43]	5	
		Crowdfunding	[4,44–61]	19	
		3D printing sharing	[62]	1	
		Electricity storage sharing	[63]	1	
	Intermediary	-		-	-
	Requester	Crowdsourcing	[5,64–80]	18	18 (11.4%)
C2C	Manufacturer	General model	[2,16,81]	3	4 (2.5%)
		Vehicle sharing	[82]	1	
	Firm	General model	[2,16,29,83–87]	8	8 (5.1%)
	Provider	General model	[2,81]	2	48 (30.1%)
		P2P accommodation	[15,88–125]	39	
		Ride sharing	[126]	1	
		Meal sharing	[127]	1	
		Crowdsourcing	[128]	1	
		Electricity storage sharing	[129,130]	2	
		Information Sharing	[131,132]	2	
	Intermediary	General model	[133–138]	6	45 (28.5%)
		Commission fee	[139–141]	3	
		Ride sharing	[142–149]	8	
		Ride hailing	[6,150–169]	21	
		Parking space sharing	[170]	1	
		WIFI sharing	[171,172]	2	
		Computing resource sharing	[173–175]	3	
		Delivery sharing	[176]	1	
	Requester	Parking space sharing	[177]	1	1 (0.6%)

Note: Because 6 of the theoretical articles discuss multiple scenarios, the sum of the counts in this table is 164.

As regards analytical approaches, 110 articles (69.6%) employ mathematical modeling, while the remainders employ quantitative analysis (43 articles, 27.2%), algorithm design (5 articles, 3.2%), and simulation (1 article, 0.6%). Pricing methodologies including supply–demand balance pricing (123 articles, 77.8%), optimization pricing (123 articles, 77.8%), auction-based pricing mechanisms (7 articles, 4.4%), fair cost allocation pricing (2 articles, 1.3%) [143], and hedonic pricing (28 articles, 17.7%) are adopted. In articles that employ mathematical modeling, to precisely characterize participants' decision processes, scholars commonly adopt multi-period models (usually two periods), jointly with backward induction, which enables them to conduct optimization, linear program, equilibrium analysis, and comparative analysis. In articles that employ quantitative analysis, scholars commonly use statistical methods, including regression analysis and hypothesis tests, to investigate the pricing in P2P accommodation. As regards theories and methodologies, hedonic pricing theory is commonly employed in P2P accommodation articles, while game theory is widely adopted in mathematical modeling articles.

4.2. Content Analysis

In the sharing economy, each participant in both the product market and sharing market can conditionally obtain pricing capacity due to the scarcity of resources. When supply is lower than demand, suppliers obtain pricing capacity (i.e., the sellers' market); otherwise, demanders obtain pricing capacity (i.e., the buyers' market). In this review, manufacturer pricing, firm pricing, provider pricing, and intermediary pricing are sellers' market scenarios, while requester pricing is the only buyers' market scenario.

4.2.1. Manufacturer Pricing

Five articles (3.2%) investigated manufacturer pricing. In the supply chain, the upstream manufacturer's optimal price and production decisions are affected by the status of the product market, which may fluctuate with the appearance of the sharing market. Therefore, following backward induction, the manufacturer should first investigate latent consumers' preferences to predict market demand, then decide the price and production accordingly.

1. C2C Model

In the C2C model, considering the product's salvage value and potential moral hazard [2], forward-looking consumers may purchase products for self-use and share when vacant, or rent from owners when needed [16]. Accordingly, the manufacturer decides the optimal price and the production capacity considering consumers' purchase decisions and costs of building the production capacity. When building costs are relatively high [16], moral hazard is relatively low, and the product's salvage value is relatively high [81]; therefore, the manufacturer can benefit from the existence of the C2C sharing market. Furthermore, for a manufacturer that produces sequential innovation products, the existence of the sharing market suppresses the market performance of old-generation products [81].

In the scenario of vehicle sharing, sharing activities can improve vehicles' fuel efficiency, thus enabling the vehicle's original equipment manufacturer (OEM) to charge a higher wholesale price [82]. This is similar to the "sharing premium" proposed by Weber [83].

2. B2C Model

In the B2C model, the firm that operates a B2C sharing business may incur product damage; therefore, the manufacturer can recycle damaged products at a recycling price. The manufacturer benefits from recycling when costs of recycling and reproduction are lower than those of directly producing new products [17]. Additionally, both the manufacturer and the firm further benefit if they maximize their profits jointly (i.e., cooperation) as opposed to separately (i.e., non-cooperation) [17].

4.2.2. Firm Pricing

Four articles (7.6%) investigated firm pricing. The firm can, on the one hand, sell products to consumers as a retailer, while, on the other hand, it can directly rent products to requesters as a provider. To maximize profit, the firm needs to strategically decide the retail price, product quality, and rental price (if they join the sharing market). In addition, sharing activities can occur inside the firm's platform (i.e., internal sharing, e.g., Car2go) or through a third-party intermediary (i.e., external sharing, e.g., Airbnb) [29].

1. C2C Model

Weber [83] proposed that sharing activities can benefit owners (i.e., the sharing premium), thus enabling the firm to charge a higher price. If the firm provides products with high marginal costs (it should be noted that production costs are commonly set as the quadratic form of product quality; therefore, high marginal costs represent high product quality), the sharing premium can lead to a lower price increment, thus weakening the price effect (i.e., the demand loss due to the price increment) [83], and the firm is stimulated to strategically improve the product quality; as a result, both the firm and consumers benefit from sharing [83,86]. Otherwise, the firm can reduce the product quality enough to disable the sharing market [87]. Additionally, under certain conditions, C2C sharing can benefit the downstream firm at the expense of the upstream manufacturer's profit loss [16].

In addition, the firm can sense, monitor, and authorize sharing activities through embedding intelligence in products (e.g., software license), so as to charge a sharing tariff [84]. This can benefit the firm if the tariff can cover the loss caused by the price effect. In this scenario, the firm benefits more if marginal costs are high and requesters are less patient [84]. When considering both the sharing tariff and the product durability, Weber [85] proposed an optimal product design to balance the durability-driven use and price effect.

On the other hand, the firm can also encroach on the C2C sharing market as a provider. In the scenario of internal C2C sharing, the firm can join the sharing market if production costs are relatively high [29]. In the scenario of external C2C sharing, the firm can join the sharing market if production costs are relatively high [29], entry costs and the population of high-use consumers are relatively low [27], or the number of requesters (i.e., the sharing culture) exceeds a certain threshold [28]. If the firm decides to join, the firm will improve their product quality [27]. Additionally, both internal and external C2C sharing can increase the sale demand, and external C2C sharing can lead to a higher rental price than internal C2C sharing [29]. Furthermore, the firm can disable the sharing market by offering the sharing service at an overly low price [28].

In the scenario of information goods sharing (e.g., software), sharing activities are nearly costless; therefore, the firm can switch from targeting individual consumers to targeting sharing groups; in this way, the firm can charge a higher price for sharing groups and thereby benefit from the increased sharing activities [30,83].

2. B2C Model

In B2C sharing, the firm can encroach on the B2C sharing market as a business provider [29]. In scenarios of both internal and external B2C sharing, the firm can join the sharing market if production costs are relatively high [29]; furthermore, the production cost threshold of joining the internal C2C sharing market is higher than that of joining the internal B2C sharing market. Additionally, the firm should reserve more products for sale, or keep the rental supply at a low level [29]. Compared to internal B2C sharing, external B2C sharing leads to a higher rental price [29].

Pei, Yan [29] also discussed a scenario that contains both C2C and B2C sharing markets; in this scenario, the firm will always join the sharing market to compete against third-party sharing firms.

4.2.3. Provider Pricing

Eighty-four articles (53.2%) investigated provider pricing. Providers in the sharing market can be individuals (i.e., C2C model) or firms (i.e., B2C model). Intuitively, due to the lack of monopoly power, the pricing capacity of providers is weaker than that of manufacturers, firms, or intermediaries, and the pricing capacity of individual providers is weaker than that of business providers.

1. C2C Model

In the C2C model, individual providers provide products or services with reasonable quality to requesters at a lower price; this advantage is more obvious, especially when requesters are variety-seeking [2]. In the C2C model, sharing activities are realized through the intermediary; in this process, information asymmetry and moral hazard may arise. Information can be disclosed through self-disclosure and the bilateral reputation system [93,109]. To eliminate moral hazard, providers can set a higher price [81], and the intermediary can design a proper deposit and insurance scheme [115].

In practice, C2C provider pricing is adopted in scenarios of P2P accommodation, ride sharing, and crowdsourcing.

a. P2P Accommodation

Research on P2P accommodation pricing (e.g., Airbnb) commonly employs hedonic pricing theory. Research data are collected from airbnb.com or insideairbnb.com, or by web-scraping; jointly with hedonic pricing models, scholars have examined the impacts of massive factors on the rental price through regression methods (ordinary least squares regression (OLS), quantile regression (QR), geographically weighted regression (GWR), and panel data regression (PD)) and machine learning methods (random forest (RF) and conditional inference tree (CTree)). By comparison, GWR performs better than OLS [116,118], while RF performs better than OLS and CTree [90].

However, inappropriate model settings or variable selections can cause inaccurate estimations. Due to the concern of endogeneity, López, Mínguez [119] employed the instrumental variable (IV) and maximum likelihood (ML) approaches. Additionally, Faye [98]

discussed incorrect estimations caused by endogeneity, sample segmentation, functional form, time heterogeneity, and spatial correlation. Accordingly, this review excluded seven articles that set multi-category variables without reference groups (e.g., accommodation type and cancellation policy), thus causing multicollinearity and resulting in incorrect estimation results.

Five types of variables were examined, namely, listing attribute, host attribute, listing reputation, rental policy, and listing location. Additionally, some macrolevel factors were also considered. Variables that significantly affect the listing's price are summarized in Appendix A Table A2, from which some validated conclusions can be summarized: the number of bedrooms, number of bathrooms, accommodating capacity, superhost badge, and overall rating have positive impacts on the rental price; the accommodation type's impact on the rental price changes from positive to negative as the renter's private space shrinks, while counter-intuitively, the number of reviews has a negative impact on the rental price.

In addition, dynamic pricing is preferred by multi-listing and experienced hosts [124]. However, although dynamic pricing is more profitable [15,100,107], a less dynamic pricing strategy is also widely adopted, under which multi-listing hosts can still profit more than nearby single-listing hosts by setting the rental price higher than that of nearby listings [15].

b. Other Scenarios

Provider pricing can also be adopted in ride sharing, crowdsourcing, and electricity storage sharing. In BlaBlaCar, experienced drivers often set lower prices [126].

In the fashion industry, the platform can adopt crowdsourcing, that is, entrant designers post samples on the platform at prices set by designers for consumers to preorder; when the number of orders reaches the minimum production quantity (MPQ), the platform arranges production. The profit is shared by both designers and the platform; therefore, to maximize the entire profit, the designer should set the price as low as possible as long as it is still profitable, and the platform should adjust the MPQ to production costs [128].

In electricity storage sharing, consumers purchase electricity storage equipment to store electricity in off-peak periods, then use it in peak periods or resell to others; therefore, electricity costs are redistributed. Employing backward induction and game theory, the consumer's optimal purchase decision can be transformed into a utility maximization problem, by solving which is the optimal rental price generated [129,130].

2. B2C Model

In the B2C model, business providers directly provide high-quality products or services at a high price to requesters [2]. Theoretically, business providers should remain risk-averse rather than risk-neutral [31]. Furthermore, it is unwise for providers to continue improving quality if related costs are already high [31].

In practice, business providers can share production capacity (crowdfunding and 3D printing sharing) or products (bike sharing, vehicle sharing, WIFI sharing, and electricity storage sharing) with requesters.

a. Crowdfunding

Compared with traditional investment, when products are costly in production but low in demand [50], crowdfunding is more friendly and more economical for small entrepreneurs to implement otherwise unfeasible projects [60]. To investigate crowdfunding, Hu, Li [4] proposed an analytical framework as follows: a creator initiates a crowdfunding project to raise production funds by sharing its production capacity to backers; backers sequentially complete two processes—they perceive the product value as high (H) or low (L), and make the joint decision as to whether their expected utility is higher than the perceived value; the project is realized if the financial target is achieved. This analytical framework lays the foundation for subsequent research.

As regards the funding scheme, the creator can choose the All or Nothing (AON) scheme or Keep It All (KIA) scheme [44,54]. If the financial target is not achieved, under AON, all funds will be refunded [44], while under KIA, the creator can keep the funds and close the project [44], or start production at a lower quality [55].

Comparing AON and KIA, AON yields a higher expected profit and a higher success rate, while under certain conditions, KIA yields a higher financial target and a larger price discrepancy [44,54,55,61]. Additionally, both AON and KIA lead to a lower quality difference than the traditional selling scenario [4,54]. KIA is more suitable when the project is scalable and the risk of starting an under-resourced project is mitigated [55]. However, if altruistic backers, who will donate the unachieved portion if the fundraising fails but the raised funds exceed a certain threshold, exist in the market, the creator will be stimulated to choose AON [53]. Furthermore, Guan, Mu [44] proposed a hybrid scheme, which allows the creator to keep a portion of funds if the fundraising fails. By comparison, AON performs better when the backer's valuation is discrete, while the hybrid scheme performs better when the backer's valuation is continuous [44].

As regards the pricing strategy, the creator can choose uniform pricing, margin pricing, volume strategy, intertemporal pricing, or menu pricing [4]; each of the pricing strategies can be optimal within certain parameter sub-spaces [4]. Additionally, under intertemporal pricing, a profit-maximizing creator can set an early bird price in the early period [46,47], or strategically adjust the price in the late period based on the market performance of the early period [49].

To fulfill different backer segments' needs, the creator can set different package sizes (e.g., large or small) [56]. The creator can raise more funds by reducing the size of the large package and narrowing the price gap between two package sizes [56]. Furthermore, when backers have different tastes, the creator can charge a higher price for taste products, but if the risk of the uncertainty of backers' preferences for quality is high, the creator should not decide product quality in the early period [45].

Apart from the sequential arrival scheme, the creator also allows backers to arrive simultaneously. When the perceived value is low or the difference between H and L is relatively small, the creator benefits more from the simultaneous arrival scheme; otherwise, adopting the sequential arrival scheme is more profitable [51].

As regards the crowdfunding intermediary, an intermediary with higher competitive strengths (i.e., lower unit costs and a lower commission fee) can help creators achieve a lower price, higher profit, and higher product quality [58]. Additionally, the intermediary should charge the same ratio for different crowdfunding projects [55].

To expand the market potential, the creator can advertise strategically, and more funds will be invested into improving the advertising level when market demand increases. Additionally, the creator tends to set a higher price when demand is low, and as demand expands, menu pricing or a lower price are preferred to guarantee the success of the project [52].

Crowdfunding is also introduced into other scenarios, such as flight ticket selling [57], cloud computing resource sharing [59], and green crowdfunding products [48], wherein it performs better than traditional models.

b. Bike Sharing

Bike sharing and vehicle sharing are typical free-floating practices, that is, requesters can rent and return bikes or vehicles at different stations. To attract more requesters, a bike sharing firm strategically prices the rental service considering the requester's time sensitivity (i.e., availability and costs) and the government subsidy [33], as well as the perception of convenience (i.e., hassle cost) [34]. Furthermore, the firm can design a proper pricing scheme to stimulate requesters to return bikes to underused stations, thus rebalancing the unbalanced inventories among stations [36]. In some cases, the price can be negative [38]. This scheme can reduce the number of unbalanced stations, while some imbalanced stations may intentionally become more unbalanced, and can be set as "hub stations" [35]. As a result, the firm can benefit from adopting this dynamic pricing scheme if costs of the price incentive are lower than those of hiring trucks and dedicated staff [35].

c. Vehicle sharing

In vehicle sharing, providers are divided into light asset firms (i.e., firms that do not possess vehicles) and heavy asset firms (i.e., firms that possess fuel-driven or electric

vehicles). Light asset firms operate vehicle sharing services by renting vehicles from a joint venture that possesses heavy inventory at a rental price [39].

As regards heavy asset firms, fuel vehicle firms can offer renting vehicles only, or renting vehicles and parking spaces to requesters, wherein parking spaces are rented from owners [43]. By comparison, the bundled scheme yields more profit and social welfare [43]. Electric vehicle (EV) firms possess EVs and limited parking and charging lots. To stimulate requesters to park EVs in underused stations, the firm can design a proper pricing scheme considering the mobility of EVs, charging scheduling, and the electricity price [41]; therefore, the pricing problem can be transformed into an optimization problem under constraints of limited parking lots, charging scheduling, and so on [40–42].

d. Other Scenarios

In 3D printing sharing, employing data mining and machine learning approaches, Pahwa and Starly [62] proposed a feasible pricing method that considers a provider's experience, capability, and reputation.

In WIFI sharing, a firm can offer renting indoor WIFI devices only, renting outdoor WIFI sharing only, and the bundled service. Due to the network's externality, if the firm can keep total costs of installing devices and providing internet services at a relatively low level, offering the bundled option is the optimal strategy [32].

In electricity storage sharing, it is costly to purchase electricity storage equipment; therefore, a profit-maximizing firm can provide both retail and rental options to consumers, benefitting both the firm and consumers [63].

4.2.4. Intermediary Pricing

Forty-five articles (28.5%) investigated intermediary pricing. In this scenario, the intermediary needs to match requesters and providers, price the sharing service according to real-time supply–demand status, and post the price to both sides; a transaction is reached if both sides accept the posted price, and the intermediary charges a commission fee. A for-profit intermediary can strategically charge a fixed or flexible commission fee to providers, requesters, or both; charging a flexible commission fee to both (i.e., dynamic pricing) is the optimal strategy [139]. To maximize the profit, the intermediary needs to ensure that the market is cleared; therefore, if the price and the usage capacity increase, or the retail price decreases, the intermediary needs to charge a higher commission fee to providers, and a lower commission fee to requesters, or vice versa [140].

In practice, the free-customers-commission strategy (FCC) and the dynamic-customers-commission strategy (DCC) are also widely adopted [139]. Under the FCC, the intermediary charges a fixed commission fee to providers only, while under the DCC, the intermediary charges a fixed commission fee to providers and charges a flexible commission fee to requesters. By comparison, DCC benefits providers but disadvantages requesters, while FCC benefits both, which explains why mature intermediaries prefer DCC, while start-up intermediaries prefer FCC [139].

When dealing with massive requests that arrive quickly, the intermediary needs to ensure timeliness, real-time updating, high efficiency, and profit maximization. Correspondingly, the intermediary can adopt dynamic pricing, surge pricing, or static pricing (see Table 2 for differences), among which adopting dynamic pricing is optimal [133,138]. Additionally, adopting surge pricing is more profitable than adopting static pricing when demand exceeds supply; otherwise, both strategies are equivalent [133]. In practice, surge pricing and static pricing are preferred due to higher feasibility [133]. Under surge pricing, it is optimal for the intermediary to increase the price when demand increases, and increase the payout ratio when requesters are losing patience [134]. When supply decreases, the intermediary can subsidize providers [135] or increase the payout ratio [134] to recruit more providers. When both demand and supply increase at nearly the same rate, the intermediary should reduce the payout ratio [134]. Additionally, under the first-come-first-serve scheme, forward-looking providers and requesters can wait for a better price;

correspondingly, the intermediary can compensate waiting costs with price adjustments, through which both providers and requesters become myopic [137].

In some scenarios, users can switch their status between providers and requesters, or transfer to other platforms [136]. Correspondingly, the intermediary needs to find the equilibrium price to balance both sides and compete against other intermediaries, through which social welfare is always improved [136].

a. Ride Sharing

Ride sharing offers a solution to congestion during peak hours [144] and the "first-mile" problem to nearby transit hubs [143]. In ride sharing, a driver can share spare seats and travel costs with only one rider (i.e., non-pooling) or at least two riders (i.e., pooling). Both sharing forms can lead to an efficient equilibrium, but considering the monopoly optimum, the social optimum, and the second-best optimum, the pooling form yields a lower travel fare than the non-pooling form [142].

As regards the pricing strategy, intermediaries can adopt auction-based pricing or rule-based pricing. Under auction-based pricing, the price is generated from the real-time auction; matching and pricing are realized simultaneously when both sides accept the auction-based price [145]. The intermediary can post drivers' biddings to nearby requesters, or post requesters' biddings to nearby drivers, while neither considers the supply–demand unbalance problem, thus decreasing requesters' utilities [146]. Correspondingly, Zhang, Wen [146] proposed a pricing mechanism based on a trade reduction double auction, which is proved to be individually rational and incentive compatible. Additionally, Yan, Lee [145] proposed a pricing mechanism based on the Vickrey–Clarke–Groves (VCG) auction, under which properties of economic efficiency, budget balance, incentive compatibility, and individual rationality are realized.

Under rule-based pricing, the price is divided into travel costs and inconvenience costs (i.e., extra travel time due to detour and extra waiting time due to possible early arrival) [143,144]. Following the mechanism design, problems of matching, pricing, and routing can be transformed into the minimization of travel costs and the maximization of users' general utilities under the constraints of individual rationality (i.e., utility non-negative and price non-negative) and incentive compatibility (i.e., truth-telling) [143].

At the operational level, Cao, Hou [147] and Zhang, Xie [148] proposed two pricing and matching algorithms. Furthermore, Yan, Zhu [149] proposed a novel dynamic pricing algorithm, named dynamic waiting, which allows drivers and riders to wait or leave before dispatch, thus mitigating the price variability and improving social welfare and system efficiency.

b. Ride Hailing

Similar to taxi drivers, a ride hailing driver takes riders to their destinations for a living. Ride hailing intermediaries include light asset intermediaries (i.e., intermediaries that do not possess vehicles) and heavy asset intermediaries (i.e., intermediaries that possess vehicles) [168]; individual providers who own vehicles can join light asset intermediaries, while non-owners can join heavy asset intermediaries [168]. Additionally, light asset intermediaries can enable non-owners to provide ride hailing services by cooperating with car-rental companies; if the commission fee is high, or the fixed payout ratio is low, this cooperation can yield a win–win–win outcome [163].

As regards the pricing strategy, the intermediary can adopt dynamic pricing, surge pricing, or static pricing (see Table 3), among which dynamic pricing maximizes the profits of both the intermediary [150,152,153,158,159] and the drivers [159]. Meanwhile, surge pricing yields a nearly optimal profit for the intermediary [157] and also benefits both the intermediary and drivers [154]; furthermore, a more flexible price and payout ratio can bring more profit to the intermediary [162]. However, when considering the utility of requesters, controversies arise. Zha, Yin [154] proposed that, under surge pricing, requesters incur utility losses caused by the expanded price, while Cachon, Daniels [157] claimed that surge pricing yields a lower price during normal hours and expanded access to ride hailing services during peak hours; therefore, surge pricing also benefits requesters.

Table 3. The intermediary's optional pricing strategies.

Price Payout Ratio	Flexible	Fixed
Flexible	Dynamic Pricing	-
Fixed	Surge Pricing	Static Pricing

Note: Payout ratio represents the ratio of a driver's wage over price.

The intermediary faces the problem of spatial–temporal supply–demand imbalance as well. To balance the supply–demand status among areas, the intermediary can first predict market demand [6,161,164], then adopt spatial discriminatory pricing accordingly (i.e., set a higher price in high-demand areas to stimulate vacant drivers to move to high-demand zones for more profits). In this way, even when demand is still not fulfilled, the intermediary still profits more from charging a higher price in less-supplied areas [6,156]. Additionally, to ensure enough drivers move to less-supplied areas, the intermediary can strategically set the surge price high enough to throttle demand in over-supplied areas [6].

As regards matching, the intermediary can adopt the first responding driver policy, which benefits requesters, or the closest driver policy, which benefits the intermediary and drivers [151]. Moreover, it should be noted that matching and pricing should be optimized jointly [169]; simply considering each side alone can lead to a subpar overall profit [160]. Therefore, Özkan and Ward [169] proposed a continuous-linear-program-based matching policy (CLP), which matches riders with farther drivers so as to maximize the number of matched pairs in the future. By comparison, this policy performs better than the closest driver policy [169].

For the intermediary that possesses autonomous EVs, the optimal pricing problem can be transformed into a profit maximization problem under the constraints of charging scheduling, electricity price, and routing [166]. In this scenario, adopting static pricing can lead to a longer waiting time and a lower profit; correspondingly, Turan, Pedarsani [166] and Al-Kanj, Nascimento [167] proposed different real-time dynamic pricing policies.

In a developing economy with limited initial assets, the intermediary should subsidize drivers to stimulate them to stay in the ride hailing system and continuously provide services. In the long run, this subsidy policy benefits both the intermediary and drivers [165].

c. Other Scenarios

In WIFI sharing, the intermediary can adopt discriminatory pricing (i.e., differentiated pricing) or uniform pricing. Under incomplete information, adopting discriminatory pricing is optimal, while adopting uniform pricing is more feasible and yields a asymptotic optimal outcome [171]. Additionally, if the discriminatory pricing scheme is simple enough (e.g., only two prices), then it is both feasible and more profitable [172].

In parking space sharing, the optimal price can be generated by solving the social cost minimization or the intermediary's profit maximization. Furthermore, the government's subsidies and regulations for the intermediary can yield a nearly social-cost-minimizing result [170].

Delivery sharing derives from ride hailing, wherein "riders" are products. In delivery sharing, the intermediary can adopt membership-based pricing, transaction-based pricing, or cross-subsidization (i.e., the platform simply subsidizes the deliveryman exactly the amount the requester pays in each transaction, and gains the profit only from the membership fee) [176]. When no time-varying discount is offered and requesters' order frequency is price-insensitive, these three strategies are equivalent. However, adopting membership-based pricing is still optimal for collecting money the earliest and maximizing the price-sensitive order frequency [176].

In computing resource sharing, Meng, Zhu [174] proposed the following pricing approach: the intermediary first announces a basic price, then providers and requesters update their optimal amount of supply and demand; the price is also updated in a timely manner, and this process is repeated until the price is stable. Additionally, Wang, Wang [173] proposed an approach based on computational latency, wherein the quality-of-experience

performance is considered. Both approaches maximize all participants' profits and ensure system efficiency [173,174].

Mostafavi and Dehghan [175] investigated a scenario in which users can share their bandwidths with others based on a non-cooperative game, and correspondingly proposed a double auction mechanism to generate the sharing price and govern the bandwidth sharing market.

4.2.5. Requester Pricing

Nineteen articles (12.0%) investigated requester pricing. Requester pricing is a typical buyers' market, wherein requesters can decide the payment. Requester pricing is adopted in scenarios of parking space sharing and crowdsourcing.

a. Parking Space Sharing

In parking space sharing, parking space owners can temporarily exchange their parking spaces with other owners for free, or rent at a rental price to the intermediary that operates the parking space sharing service [177]. Based on first-price and second-price sealed auctions, Tan, Xu [177] proposed a sequential auction mechanism, which enables the intermediary to allocate parking spaces to requesters at a price; the allocation price can then be referenced by the intermediary when setting the rental price.

b. Crowdsourcing

Crowdsourcing offers requesters an alternative solution to accomplishing massive and repetitive tasks. In crowdsourcing, the requester posts tasks and corresponding rewards on a platform for workers to accomplish and receive. Note that adopting monetary rewards performs better than adopting non-monetary rewards [77]. Therefore, determining how to price massive tasks profitably and efficiently is important; thus, automated agents are employed. Azaria, Aumann [72] proposed two automated agents, namely, the reservation-price-based agent and the no-bargaining agent, the simulation results of which show that both automated agents outperform human experts.

To ensure task assignment, task accomplishment, budget control, and quality control, the requester needs to price tasks strategically. Based on an asymmetric all-pay auction, Luo, Kanhere [79] proposed a reward-based incentive mechanism with properties of strategy autonomy, individual rationality, and incentive compatibility; under this mechanism, heterogeneous workers behave homogeneously. Gonen, Raban [5] proposed a descending pricing function that is sensitive to the supply–demand status, under which workers accomplish their tasks in a timely and efficient manner.

Workers' payments are decided based on their arrival sequences [66], their reputation observed from their previous work [71,75], and the quality of accomplished tasks [66,73,74,76]. In some cases, workers can bid their expected payments, and the requester decides workers' actual payments by considering their biddings and reputation jointly [75]. To incentivize workers to bid truthfully, Duan, Yan [78] designed a VCG-auction-based mechanism, which is proved to be individually rational and computationally efficient. Furthermore, after tasks are accomplished, the requester can reprice tasks based on the quality of accomplished tasks, so as to control quality and costs [68].

In addition, employing regression methods, Li, Li [67] and Hao, Guo [65] examined the impacts of factors including workers' average distance from the given task point, distance between locations of tasks, workers' credit and reputation, workers' density within the given area, and tasks' density within the given area.

Imbalance problems occur if workers strategically accomplish nearby tasks (e.g., sensing geographical data or photographs). To encourage workers to accomplish remote tasks, the requester can announce a price in the early period, and reprice the unaccomplished tasks in the late period [69]. However, this pricing scheme may cause an expanded budget and reduce the attractiveness of early period tasks; therefore, Shi, Zhao [70] proposed a price mediation mechanism based on an optimal branch-and-bound algorithm, under which requesters' profits, workers' profits, and social welfare are maximized. Furthermore,

Zhou, Chen [64] also proposed a novel dynamic pricing iterative algorithm that prices tasks considering their supply–demand status.

In hierarchical crowdsourcing networks, imbalance problems occur as a herding phenomenon (i.e., a portion of reputable workers are overloaded, while others are idle). Correspondingly, Yu, Miao [80] proposed a Lyapunov-optimization-based decision support approach, which allocates tasks and payments reasonably, considering workers' reputation, workloads, eagerness to work, and trust relationships with others.

5. Discussions

5.1. Research Gaps

As reviewed above, employing empirical and mathematical approaches, scholars have successfully investigated pricing strategies in various SE scenarios. However, there are still some gaps to fill. First, in mathematical modeling articles, scholars commonly assume that the market information is complete, while information asymmetry is closer to reality. Second, the existing literature mainly discusses interactions among different parties (e.g., providers and requesters, firms and consumers), while competitions within the same party (e.g., competitions among providers) are rarely discussed. Third, in some empirical articles, dependent variables and independent variables are causal to each other (i.e., mutual causality); therefore, endogeneity arises. Additionally, some of the literature directly compares the estimation results of the same model with different sample data, and such comparison conclusions are statistically unreliable.

5.1.1. Manufacturer Pricing

In the supply chain, the manufacturer needs to collect market information as the basis of setting the optimal price and production capacity. Information can be collected by the manufacturer at a cost, and/or by sharing from the downstream firm who has limited information (e.g., sales data). To incentivize the firm to share the information truthfully, a properly designed mechanism is needed. If the downstream firm chooses not to share, the manufacturer can still infer the information from the firm's retail price. However, the manufacturer's optimal information sharing strategy and mechanism design are still uninvestigated. This interaction can be characterized as a coopetition game by employing backward induction and signaling games.

5.1.2. Firm Pricing

As mentioned above, the downstream firm and the manufacturer can strategically choose whether to share the market information with each other. The firm can also infer the information from the wholesale price, and then decide their retail price accordingly. Furthermore, if the firm chooses to join the sharing market, it also needs to collect the sharing market's information by itself at a cost or by inferring it from competitors' pricing decisions (e.g., incumbent third-party sharing platforms). Similarly, these coopetition or competition games can also be characterized by employing backward induction and signaling games. Moreover, it is worth mentioning that the signaling game has been widely employed in research on supply chain management [178] and online platforms [179,180]; however, it has not been introduced into research on SE.

5.1.3. Provider Pricing

Weber [115] discussed the ex-post information asymmetry (i.e., moral hazard) and the external competition (i.e., the competition between Airbnb listings and hotels) in the scenario of P2P accommodation, while the internal competition (i.e., competitions among providers in the sharing market) is not discussed thoroughly. Furthermore, in B2C sharing, moral hazard, the competition among providers, and their effects on providers' pricing decisions are not discussed. As regards research on specific scenarios, such as P2P accommodation, bike sharing, vehicle sharing, and crowdfunding, theoretical and empirical gaps still exist.

1. P2P Accommodation

In practice, Airbnb listings and hotels compete against each other [115], which implies that mutual causality exists between their pricing decisions; therefore, endogeneity arises. To characterize this pricing interaction and eliminate endogeneity, a simultaneous equation model (SEM) can be employed. Additionally, some of the literature directly compares the estimation results of the same model with different sample data, and such comparison conclusions are statistically unconvincing. There are three approaches to compare estimation results of the same model with different sample data: (1) Chow test (i.e., introducing a dummy variable and cross term), (2) SUEST (i.e., hypothesis test based on seemingly unrelated regression), and (3) Fisher's permutation test (i.e., hypothesis test based on regressions of bootstrap samples). With these models and approaches, a more accurate and reliable regression analysis can be conducted.

Theoretically, due to the lack of market information and professionality, it is not easy for individual hosts to price their listings accurately. Contrarily, Airbnb holds the market information (e.g., sales data) and can, therefore, post a suggested price to hosts as a reference. Correspondingly, hosts may accept the suggested price, infer the market information if they value it as reasonable, or ignore and price listings independently if they value it as overly low. However, how Airbnb decides the suggested price, how hosts react to the suggested price, how hosts advertise their listings (i.e., the truthfulness of self-disclosure), and how hosts decide the optimal price are still uninvestigated problems. Furthermore, the internal competition (i.e., the competition among nearby Airbnb listings) and the external competition (i.e., the competition between Airbnb listings and hotels) under asymmetry of information are still uninvestigated. These problems can be characterized by employing cheap talk and signaling games.

2. Bike Sharing and Vehicle Sharing

Some scholars mention government subsidies on bike sharing [33] and electric vehicles [168], while the government's subsidy strategy is not discussed. In scenarios of bike sharing, bikes are often parked in public areas; according to Coase's theory of property [181], to avoid "the tragedy of the commons", the government can clarify the ownership of the public area's property right. On the other hand, the government can also subsidize firms, requesters, or both to improve social welfare, but which subsidy strategy is optimal in terms of budget and operation is still not discussed. Additionally, scholars have investigated the competition between firms and the public transportation system [33], while the competition among firms has not been investigated, nor has the moral hazard that firms face (e.g., potential damage to bikes and vehicles).

In practice, firms often adopt discriminatory pricing in different market segments. Inspired by hedonic pricing theory, a hedonic-pricing-like model can be employed to empirically examine the impacts of a product's attributes (e.g., vehicle information, covered area, and sharing policy) and users' reviews on the sharing price.

3. Crowdfunding

In crowdfunding, backers are usually unaware of product quality [55]; therefore, ex-post information asymmetry arises. Backers may change their minds if they consider the risk of quality uncertainty; thus, the creator needs to adjust their funding and pricing strategies accordingly. Furthermore, the impacts of the creator's pricing strategy, funding strategy, product design, and other attributes (e.g., reviews, ratings, product descriptions, and number of product photos) on the crowdfunding project's success rate at different price intervals have not been investigated. To investigate such impacts, discrete choice models (DCM) (e.g., logistic model and probit model) can be employed.

5.1.4. Intermediary Pricing

In intermediary pricing, ex-post information asymmetry can arise if either providers or requesters do not fulfill their obligations. Such moral hazard can affect the decisions of both sides, thus causing supply–demand status changes in the sharing market, and results in price fluctuation. Additionally, the role that the intermediary can play in eliminating

moral hazard has been discussed in provider pricing by Weber [115], while similar research remains absent in intermediary pricing.

• → Ride Sharing and Ride Hailing

If drivers or riders do not fulfill their obligations, such as canceling orders or detouring intentionally, which compensation and punishment mechanism can be designed has still not been discussed. Additionally, in practice, the intermediary controls service quality by issuing licenses, scheduling routes, and installing monitors, which generates more operating costs, while these efforts' effects on users' purchase decisions and the intermediary's tradeoff have not been investigated. Furthermore, the internal competition (i.e., the competition among nearby drivers) and the external competition (i.e., the competition between ride sharing and ride hailing and the taxi industry) have not been investigated either.

Despite the fruitfulness of the theoretical research, empirical research is rarely conducted, including research on the profitability difference between dynamic pricing (e.g., ride hailing platforms) and static pricing (e.g., the traditional taxi industry). Battifarano and Qian [161] empirically validated that the surge multiplier is affected by weather conditions, traffic conditions, and public events, while regional factors (e.g., the departure and destination locations and trip distance), time factors (e.g., peak hours), and macrofactors (e.g., local income level, local taxi price) were not examined. Additionally, Farajallah, Hammond [126] examined factors that affect a driver's pricing decision in BlaBlaCar by adopting a hedonic-pricing-like model, which inspires the idea that hedonic-pricing-like models can also be employed to empirically investigate pricing strategies of different market segmentations (e.g., express service and select service provided by Didi).

5.1.5. Requester Pricing

Different from other scenarios, requester pricing is a typical buyers' market. In requester pricing, the requester can directly decide prices of tasks when their pricing capacity is strong enough or post their requirements for workers to bid if their pricing capacity is weak. In the second scenario, the reverse auction can be employed to design a proper mechanism to stimulate workers to bid truthfully.

5.2. Research Extension

Indeed, practices of SE are becoming increasingly mature and diverse. However, it is still worth exploring whether the business form of SE can be applied to more traditional business scenarios and whether new pricing methodologies can be applied to existing sharing scenarios. Moreover, under the back-and-forth situation of COVID-19, how participants, especially beneficiaries, are affected by the epidemic, and what they should do to survive the dilemma remain challenging questions.

5.2.1. Scenario Extension

In some scenarios, providers will face vast requesters in the predictable future (e.g., seasonal tourism); therefore, shared products can be in extreme scarcity. In addition to dynamic pricing, auction-based pricing is also feasible in such scenarios, but it is still not discussed. Contrarily, when no provider shows intention to share, the requester can increase the posted price to stimulate latent providers or adopt a reverse-auction-based mechanism, which is similar to crowdsourcing, but related research remains absent. In addition to crowdfunding flights [57], other sharing scenarios, such as crowdfunding a long-term rental apartment, are also worth being investigated, and other new practices are also worth discussing, such as sharing a portable charger.

5.2.2. Under COVID-19

What impacts has the epidemic caused? What actions should be taken under the "new normal" situation [182]? What will SE be like in the post-epidemic era? Under the COVID-19 situation, these three questions need to be answered. In scenarios that

are affected by the epidemic the most (e.g., P2P accommodation and ride sharing), to assess the epidemic's impacts, difference-in-difference (DID) and regression discontinuity design (RDD) approaches can be employed. As regards the unemployment caused by the epidemic, SE can offer more jobs to the unemployed, similar to what SE offered after the financial crisis in 2008. Furthermore, in the post-epidemic era, how SE will be organized (e.g., more remote and self-service activities and consumption, and less direct contact) is an interesting and practical topic.

5.3. Limitations

Despite the work this review has accomplished, there are still some limitations. First, although this review identified 30 scenarios, only seven scenarios were investigated intensively; therefore, other scenarios are neither sufficiently investigated nor sufficiently reviewed. Second, due to the space limitation, technical details of the existing literature are not fully presented; if readers are interested in technical details, please refer to related original articles. Third, due to the lack of related systematic knowledge in some fields (e.g., algorithm), this review is not able to provide comments, or propose gaps or future directions from these perspectives.

6. Conclusions

Following the PRISMA protocol [19], this study conducted a systematic literature review and content analysis on pricing strategies in SE. First, an extended definition covering B2C and C2C models, and an extended model structure of SE covering the entire supply chain, were proposed. Based on the proposed definition and model structure, 158 identified articles were grouped into nine sub-models covering 30 scenarios (shown in Table 3). After the content analysis, theories, methods, and conclusions of existing articles were reviewed. As a result, first, scenarios of P2P accommodation, ride sharing and ride hailing, bike sharing and vehicle sharing, crowdfunding, and crowdsourcing were intensively investigated. Second, in the existing literature, pricing methodologies including supply–demand balance pricing, fair cost allocation pricing, optimization pricing, auction-based pricing mechanisms [143], and hedonic pricing are employed. Third, in mathematical modeling, based on backward induction and game theory, multiple analytical approaches, including optimization, linear programming, equilibrium analysis, and comparative analysis, are widely conducted; in empirical analyses (mostly research on P2P accommodation), based on hedonic pricing theory, regression analysis and hypothesis tests are commonly employed. More importantly, conclusions and technical details are reviewed and summarized in the Section 4.

Based on the content analysis, some research gaps and a future agenda are proposed from the perspectives of information asymmetry, market competition, and empirical approaches. First, even though information asymmetry and market competition are closer to reality, they are rarely discussed in the identified articles. In fact, the signaling game, cheap talk, and other game theoretic models have been widely employed in research on information asymmetry and market competition in the fields of online platform and supply chain management; therefore, the sharing economy, a business model based on online platforms and upstream supply chains, can also be investigated with analytical paradigms applied in the above-mentioned fields. Second, this review suggests some empirical approaches for quantitative analysis, including DCM, SEM, DID, RDD, Chow test, SUEST, and Fisher's permutation test, the employment of which can generate statistically reliable outcomes. Meanwhile, this article suggests some pricing mechanisms that are worth introducing in existing scenarios (e.g., applying auction to provider pricing and applying reverse auction to crowdsourcing) and also proposes some scenarios that still lack investigation (e.g., sharing long-term apartment rental and sharing a portable charger). Finally, in the post-epidemic era, it is important and practical to discuss the impacts of the epidemic, reactions of SE participants, and new possible forms to which SE can be expanded. In this regard, it is

always encouraging to consider the situation after the epidemic and measures to eliminate the losses it has caused.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Distribution of reviews by field.

Theme	Source
Framework and Scenario Distribution	[3,8,23,183–190]
Definition and Conceptualization	[14,24,191–193]
Business Models	[21,194–196]
Sharing Practices	[197,198]
Tourism and Hospitality	[8,199,200]
Peer-to-Peer(P2P) Accommodation	[9–11,26,182,201–205]
Airbnb	[11,184]
Home Sharing	[182,205]
Computing	[7]
Digital Platforms	[206]
Ride-Sharing and Ride-Sourcing	[12,22,207–210]
Matching	[208]
Collaborative Fashion Consumption	[25,211]
Motivation	[13,212,213]
Trust	[13,213]
Impacts and Externalities	[200,207,211,214]
Sustainability	[193,196,209,214]
Citation Analysis	[215–217]

Note: This search was implemented in Dec 2020 by searching terms "sharing economy" and "review" in Scopus database; 51 literature reviews were identified.

Table A2. Summarized independent variables in empirical articles (dependent variable: price).

Category	Variable		Effect	Reference	Count	Total
Listing Attribute	Room Type	House	-	[88]	1	1
	Number of Bedrooms		+	[88,89,91,94,96,97,99,101,106,110–112,114,117,121,123]	16	16
	Number of Beds		-	[90]	1	3
			+	[94,103]	2	
	Number of Bathroom		+	[88–91,94,99,101,106,110–112,114,120,123]	14	14
	Amenity Index		+	[120,123]	2	2
	Hot Tub		+	[94]	1	1
	Lock on Bedroom Door		-	[90]	1	1
	Free Parking		+	[88,89,94,99,114]	5	6
			-	[90]	1	
	Paid Parking		-	[90]	1	1
	Pool		+	[94,99]	2	2
	Gym		+	[99]	1	1
	Real Bed		+	[88,114]	2	2
	WIFI		+	[88]	2	2
	Number of Accommodation Photos		+	[96,99,111]	3	3
	Perceived Value of Apartment Photos		+	[97]	1	1
	Accommodating Capacity		+	[88–91,99,101,110,111,114,117,120,123]	12	12
	Accommodation Type	Entire Home	+	[88,89,96,103,111,114,120,121]	8	18
		Private Room	+	[88,89,96,114]	4	
			-	[91,99,110,123]	4	
		Shared Room	-	[99,101]	2	
	Breakfast		+	[88,89]	2	3
			-	[114]	1	
	Kids and Family Friendly		+	[89,90]	2	2
	Doorman		+	[89]	1	1
	Elevator		+	[90,91,94]	3	3
	Indoor Fireplace		+	[90]	1	1
	Cable TV		+	[90]	1	1
	Suitable for Events		+	[90]	1	1
	Carbon Monoxide Detector		+	[90]	1	1
	First Aid Kit		+	[90]	1	1
Host Attribute	Number of Listings		+	[89]	3	4
			-	[94,110,114]	1	
	Verification		+	[88,114]	2	2
	Profile Picture		-	[114]	1	1
	Perceived Value of Profile Picture	Trustworthy	+	[88,96,97]	3	7
			-	[121]	1	
		Attractive	+	[88,121]	2	
		Smile Intensity	+	[121]	1	
	Response Time		-	[91]	1	1
	Response Rate		+	[110,111]	2	2
	Race	Black	-	[121]	1	1
	Superhost Badge		+	[88,89,94,96,99,101,110,111,114,120,123]	11	11
	Professional (Multi-Listings)		+	[99,103]	2	3
			-	[111]	1	
	Host Membership Month		+	[89]	1	1

Table A2. *Cont.*

Category	Variable		Effect	Reference	Count	Total
Listing Reputation	Guest Rating Percent		-	[94]	1	1
	Number of Reviews		U-Shape	[88]	1	14
			-	[89,90,94,96,99,101,103,110,111,114,116,120,123]	13	
	Overall Rating		+	[88,89,99,110,111,114,117]	7	12
			-	[90,91,101,116,123]	5	
Rental Policy	Rental Policy Index		+	[120]	1	1
	Cancellation Policy	Strict	+	[101]	3	4
			-	[110,111,114]	1	
		Moderate	+	[110,111,114]	3	3
		Flexible	+	[88]	1	1
	Guest's Profile Photo Required		+	[114,120]	2	3
			-	[88]	1	
	Guest's Phone Verification		+	[88,114]	2	2
	Instant Bookable		+	[111]	1	7
			-	[88,89,94,99,114,123]	6	
	Smoking Allowed		-	[88,114]	2	2
	Pets Allowed		-	[94]	1	1
	Cleaning Fee		+	[91]	1	1
	Minimum Stay		-	[110]	1	1
Listing Location	Neighborhood Value		-	[101]	1	1
	Average Rental Price in District		+	[121]	1	1
	Number of Airbnb Listings in the Same District		+	[88,89]	2	3
			-	[101]	1	
	Price of Surrounding Hotels		+	[106]	1	1
	Price of Surrounding Airbnb Listings		+	[120]	1	1
	Number of Surrounding Competitors		-	[112]	1	1
		Number of Surrounding Airbnb Listings	+	[117,120]	2	2
	Distance to Tourism Attraction		+	[101,106]	2	7
			-	[89,94,116,120,123]	5	
	Located within Sightseeing		+	[112]	1	1
	Distance to City Center		-	[94,99,106,111,114]	5	5
	Distance to the Nearest Highway		-	[88]	1	1
	Pedestrian Density		+	[94]	1	1
	Noise		-	[94]	1	1
	Distance to Subway		-	[123]	1	1
Macro Factors	Population		-	[117]	1	1
	Unemployment Rate		-	[117]	1	1
	Disposable Income		+	[117]	1	1

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