

Justice Pathways in Algorithmic Pricing: A Conceptual Framework and a Meta-Analytic Synthesis of Consumer Fairness Reactions

Zejun SHUAI*, Charlotte GASTON-BRETON, Sandrine MACÉ

ESCP Business School, Paris, France

*Corresponding author: zejun.shuai@edu.escp.eu

Abstract

Algorithmic pricing (AP) is expanding across many sectors, yet consumer reactions remain divergent in direction (positive or negative) and in nature (cognitive, affective, conative, or behavioural). This research focuses on three conditions of AP — price position, transparency, and data type — and proposes a three-layer conceptual framework: a cognitive antecedent (trust, suspicion, perceived value) upstream of three perceived justice dimensions (distributive, procedural, and overall), which in turn mediate the relationship between AP characteristics and consumer reactions. The framework is tested through meta-analytic structural equation modelling (MASEM) drawing on 80 published empirical studies (89 independent samples; $N = 74,776$ consumers; 211 effect-size correlations; 2010–2025) and pits eight competing structural specifications against one another. Results indicate that AP does not directly activate distributive justice ($\bar{r} = +.012$, n.s.), while the perceived-fairness pathway robustly predicts positive affective reactions ($\bar{r} = +.624$, $k = 4$) and conative reactions ($\bar{r} = +.270$, $k = 23$). The sequential cognition \rightarrow justice \rightarrow reactions architecture defeats the parallel specification ($\Delta BIC = 41.5$; Raftery, 1995), revealing a mechanism hitherto absent from the literature.

Keywords: Algorithmic pricing; Price fairness; Justice theory; Meta-analysis; MASEM

La Justice et ses Mécanismes dans la Tarification Algorithmique : Conceptualisation et Synthèse Méta-analytique des Réactions des Consommateurs en Matière d'Équité Tarifaire

Résumé

La tarification algorithmique (TA) se développe dans de nombreux secteurs, et les réactions des consommateurs apparaissent divergentes en direction (positives ou négatives) et en nature (cognitive, affective, conative ou comportementale). Cette recherche se concentre sur trois conditions de la TA — positionnement tarifaire, transparence et type de données utilisées — et propose un cadre conceptuel à trois couches : un antécédent cognitif (confiance, suspicion, valeur perçue) en amont des trois dimensions de la justice perçue (distributive, procédurale et globale), qui médient ensuite la relation entre les caractéristiques de la TA et les réactions des consommateurs. Le cadre est testé par une méta-analyse en équations structurelles (MASEM) portant sur 80 études empiriques publiées (89 échantillons indépendants ; $N = 74\,776$ consommateurs ; 211 tailles d'effet ; 2010–2025) et confronte huit spécifications structurelles concurrentes. Les résultats indiquent que la TA n'active pas directement la justice distributive ($\bar{r} = +0,012$, n.s.), tandis que la voie médiée par l'équité perçue prédit robustement les réactions affectives positives ($\bar{r} = +0,624$, $k = 4$) et conatives ($\bar{r} = +0,270$, $k = 23$). L'architecture séquentielle cognition \rightarrow justice \rightarrow réactions l'emporte sur la spécification parallèle ($\Delta BIC = 41,5$; Raftery, 1995), révélant un mécanisme jusqu'ici absent de la littérature.

Mots-clés : Tarification algorithmique ; Équité tarifaire ; Théorie de la justice ; Méta-analyse ; MASEM

1. Introduction

Algorithmic pricing (AP) functions by real-time automated, data-driven adjustment of prices based on demand signals, consumer characteristics, or competitive conditions (Spann et al., 2025). It encompasses two principal forms: dynamic pricing (DP), which adjusts prices over time in response to aggregate market conditions, and personalised pricing (PP), which sets individual prices based on consumer-specific data (Seele et al., 2021). The commercial deployment of AP has accelerated across industries, from established applications in airlines and hospitality to increasingly granular adoption in e-commerce, ride-hailing, retail, and grocery (Kopalle et al., 2023), a trajectory that continues as algorithmic tools become accessible to firms of all sizes (Vomberg et al., 2024). Nevertheless, consumer acceptance of AP is far from uniform. Consumers sometimes habituate to AP and accept it as a market norm (e.g., loyal ride-hailing users who tolerate surge pricing; Huarng & Yu, 2020), particularly when AP cues are salient or the outcome appears demand-driven (Vomberg et al., 2024; Choi et al., 2023); in other contexts, PP triggers negative moral judgements and seller suspicion even among consumers who receive a favourable price (Ohlwein & Bruno, 2025), and DP generates complaints that erode a substantial share of the firm's revenue gain (Xu et al., 2025).

A growing body of empirical work has examined the conditions under which consumers evaluate AP, yet the evidence remains fragmented and contradictory. Recent reviews have mapped the strategic (Spann et al., 2025), normative (Starke et al., 2022), ethical (Seele et al., 2021), and operational (Chenavaz & Dimitrov, 2025) aspects of algorithmic price-setting, with each having taken the firm, the algorithm, or the mechanism as its focal object. Consumer responses to AP, rooted in moral judgements and commonly measured by perceived fairness, span three outcome domains: affective responses such as anger, worry, gratitude (Xia & Monroe, 2017; Garbarino & Maxwell, 2010), conative responses such as purchase intent and switching (Malc et al., 2016), and behavioural responses such as platform (dis)continuance and complaint (Cui et al., 2022). For each of these domains, findings remain inconsistent across price position, transparency, and data type. Fairness perceptions reverse direction between advantaged and disadvantaged positions across studies (Ohlwein & Bruno, 2025; Wang & Krishna, 2012; Haws & Bearden, 2006); disclosing the algorithm can either mitigate negative reactions (Bhattarai et al., 2023) or intensify them (Bambauer-Sachse & Young, 2024); personal demographic data sometimes triggers stronger aversion than behavioural tracking data (Hufnagel et al., 2022; Yan et al., 2025). Without a synthesis that traces the evaluative mechanism and tests boundary conditions, these inconsistencies remain indistinguishable from measurement and design artefacts (Podsakoff et al., 2016).

Prior literature has positioned consumer moral judgement as central to understanding AP's effects on consumer responses, that consumers do not react to an AP directly but via the moral judgement they form about it (Bambauer-Sachse & Young, 2024; Ohlwein & Bruno, 2025). However, most AP studies treat moral judgement as a unidimensional fairness construct, failing to disaggregate the divergent consumer responses. We propose to update the state-of-the-art justice framework with three theoretical refinements that translate moral assessments of AP into bounded, empirically tractable evaluative dimensions (cf. Suddaby, 2010). First, distributive justice (DJ, whether the price outcome is equitable) and procedural justice (PJ, whether the process is legitimate), the two dimensions established by Xia, Monroe & Cox (2004) are retained as separate mediators. Second, when primary studies do not separate DJ from PJ, we admit overall fairness (OF) as an aggregate evaluative dimension. Third, and centrally, we position a cognitive antecedent layer (COG — trust, suspicion, betrayal-suspicion, perceived value) upstream of the justice judgement, following appraisal theory (Lazarus, 1991), referent-cognitions theory (Folger, 1986), and the interactional-procedural sequence in justice research (Bies & Moag, 1986). Consumers first form a cognitive appraisal of the algorithmic stimulus before mapping the outcome onto fairness norms — a temporal sequence that the two-dimensional DJ–PJ lens cannot capture.

This three-layer architecture — algorithmic stimulus → cognitive antecedent (COG) → justice evaluation (DJ / PJ / OF) → consumer reaction (AFF / CON / BEH) — reframes what appears as inconsistency across studies as differential activation of distinct evaluative layers under distinct AP conditions. We examine whether price position primarily activates distributive concerns, transparency activates procedural concerns, and data type activates the cognitive antecedent layer. Distinguishing these layers within a single structural model offers a theoretical path to resolving the contradictions and specifying the mediating mechanism through which AP conditions translate into divergent affective, conative, and behavioural outcomes. The proposed conceptual framework is summarised in Figure 1.

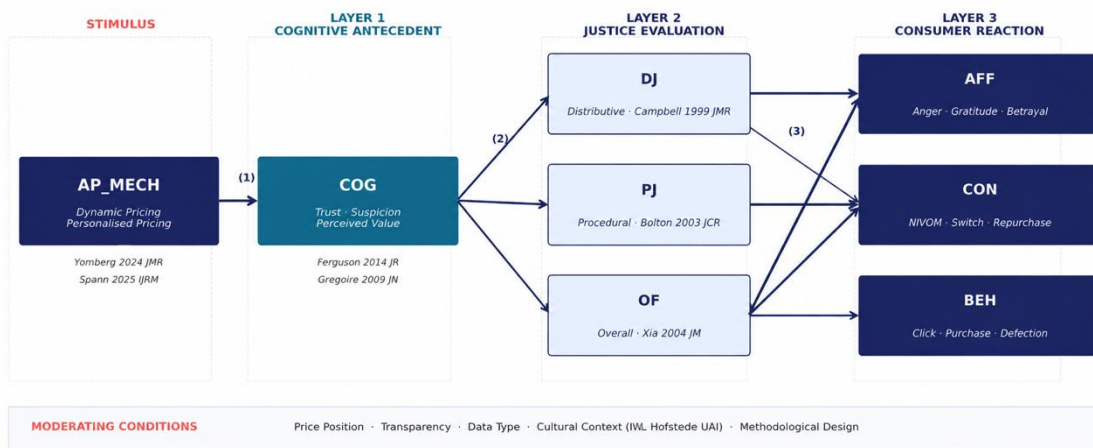


Figure 1. Three-Layer Conceptual Framework: Justice Pathways from Algorithmic Pricing to Consumer Outcomes.

Solid arrows represent the hypothesised structural sequence (M2 in §2.3); Anchor citations beneath each construct identify the dominant primary-study scale.

The empirical inconsistencies above, combined with the absence of a tested three-layer mediating framework, create a methodological demand that no single primary study can satisfy. Meta-analytic structural equation modelling (MASEM) is the method equipped to do this: it quantifies the direction and strength of AP’s effects on consumer outcomes, tests whether DJ, PJ, OF, and COG account for the variance individual studies leave unexplained, and estimates the contingency of these paths across moderating conditions (Cheung & Chan, 2005; Cheung, 2015; Borenstein et al., 2009). We report such a synthesis, drawing on 80 published empirical studies yielding 211 effect-size correlations (89 samples; N = 74,776; 2010–2025), constituting the first meta-analytic test of justice-based mediation in the AP literature.

2. Methodology

2.1 Search strategy and sample

We conducted a PRISMA-compliant systematic literature search across Web of Science (all collections), Scopus, EBSCO (Business Source Complete and PsycINFO), and ProQuest, using Boolean syntax combining algorithmic pricing terms with consumer terms. The initial search yielded over 27,000 records before deduplication. After title–abstract screening and full-text assessment against predefined inclusion criteria, the final sample comprises 80 studies, 89 independent samples, and 211 effect-size correlations covering 74,776 consumers (2010–2025). The full PRISMA flow chart is provided in Appendix A.

2.2 Coding and variables

Each effect size was coded along the three-layer architecture. The independent variable was classified by one of three AP conditions: price position (advantaged vs. disadvantaged), transparency (algorithm disclosed vs. concealed), and data type (behavioural vs. demographic vs. biometric). The cognitive-antecedent layer (COG; $k = 51$) captured trust, suspicion, betrayal-suspicion, and perceived value. The justice layer comprised DJ ($k = 28$), PJ ($k = 16$), and OF ($k = 28$). The outcome layer was classified by domain: AFF ($k = 34$), CON ($k = 51$), and BEH ($k = 8$). Moderators include AP type, industry, cultural context (Hofstede; Inglehart-Welzel), study design, and publication-quality tier. Full variable definitions, scale anchors, and primary-study sample items are provided in Appendix B.

2.3 Analytic approach

We employ a three-stage hybrid MASEM pipeline. Stage 1 — univariate Hedges-Olkin meta-analysis (HOMA; Hedges & Olkin, 1985; Borenstein et al., 2009) — pools bivariate Fisher-Z-transformed correlations under inverse-variance REML weighting. Stage 2 — meta-analytic regression analysis (MARA; Faramarzi & Bhattacharya, 2024; Barari et al., 2025) — regresses Fisher-Z-transformed effects on 35 + paper-level moderators. Stage 3 — two-stage structural equation modelling (TSSEM; Cheung & Chan, 2005; Cheung, 2015) — fits the hypothesised three-layer model on the pooled correlation matrix. Heterogeneity is assessed via I^2 ; publication bias via funnel plots and Egger's test.

Following best practice in meta-analytic structural modelling (Desveaud, Mandler & Eisend, 2024), we compare eight rival structural specifications against AIC and BIC criteria (Burnham & Anderson, 2002; Raftery, 1995): M1 Classical Justice; M2 Three-Layer Sequential (our contribution); M3 Hierarchical Fairness; M4 Pure CAB chain without justice (falsification); M5 Dual-Path; M6 Integrated Saturated; M7 Reverse Causal (falsification); M8 Parallel Competing. Model comparison uses $\Delta BIC \geq 10$ as very-strong evidence (Raftery, 1995) and Hu-Bentler (1999) cut-offs ($CFI \geq .95$, $RMSEA \leq .06$). The full eight-model comparison appears in Appendix E.

3. Results

Stage 1 HOMA reveals that the direct effect of AP on distributive justice is statistically null ($k = 14$, $\bar{r} = +.012$, n.s.), challenging the literature's implicit assumption that algorithmic pricing inherently triggers fairness violations. The outcome-fairness pathway is robust: OF \times CON pools to $\bar{r} = +.270$ ($k = 23$, $p < .05$), OF \times AFF_POS to $\bar{r} = +.624$ ($k = 4$, $p < .01$). Across all 28 estimable pooled cells, \bar{r} ranges from $-.340$ to $+.624$ (full table in Appendix C). The cognitive-antecedent layer correlates with AP at $\bar{r} = +.284$ ($k = 23$, $p < .001$), supporting its Layer-1 placement upstream of justice.

Stage 2 MARA identifies eighteen moderators significant at $p < .10$ (full table in Appendix D). Cultural context dominates: IW Catholic-Europe shifts the pooled effect by $\beta = -.664$ ($p < .001$) relative to the English-Speaking baseline, and Hofstede Uncertainty Avoidance attenuates the effect ($\beta = -.063$, $p < .05$). Methodological moderators matter substantially: studies without random assignment report weaker effects ($\beta = -.260$, $p < .05$), sample-age heterogeneity attenuates magnitude ($\beta = -.136$, $p < .01$), and larger sample sizes are associated with smaller effects ($\beta = -.068$, $p < .05$). Publication-bias indicators are visible: FT50 journals and ESCP Alpha-tier outlets report stronger effects ($\beta = +.380$ and $+.398$, $p < .05$).

Stage 3 TSSEM fits all eight competing specifications on the pooled correlation matrix ($k = 76$ papers, $\Sigma N = 27,932$). The BIC ranking is decisive (lower = better): M3 Hierarchical Fairness wins at BIC = -151.34; M2 Three-Layer Sequential is second at BIC = -110.50; M1 Classical Justice is third at BIC = -106.05; M4 CAB no-justice is worst at BIC = -33.50 — a 77-point gap that constitutes very-strong evidence (Raftery, 1995) that justice dimensions mediate the AP-to-outcome link. M2 beats M8 Parallel Competing by $\Delta BIC = 41.55$ — very-strong evidence that cognition operates upstream of fairness rather than in parallel. M7 (Reverse Causal) fails identification on 10 paths, ruling out a reverse-direction explanation. The full fit-comparison table is in Appendix E and the seven-model SEM montage in Appendix G.

4. Contributions

This research offers three contributions. First, it reframes the AP acceptance debate from whether consumers accept AP to how and through which pathway they form their evaluative responses. The evidence that $AP \times DJ$ is empirically null ($\bar{r} = +.012$, n.s.) while the OF-mediated pathway is robust ($\bar{r} = +.270$ to $+.624$) shows that the field's inconsistencies reflect differential activation of justice dimensions rather than true contradictions.

Second, it provides the first empirically tested three-layer justice framework for the AP context, with the cognitive antecedent layer positioned upstream of justice. M2 beats M8 by $\Delta BIC = 41.55$ — very-strong evidence under Raftery (1995) — and M3 wins the parsimony comparison, both consistent with the three-layer claim.

Third, it constitutes the first comprehensive MASEM in the AP literature, with three orthogonal substantive findings: algorithmic pricing alone does not trigger justice perceptions (the leverage point is perceived fairness, not algorithm-ness); cultural context is the dominant moderator (Catholic-Europe $\beta = -.664$, $p < .001$); and methodological design accounts for a substantial share of cross-study heterogeneity.

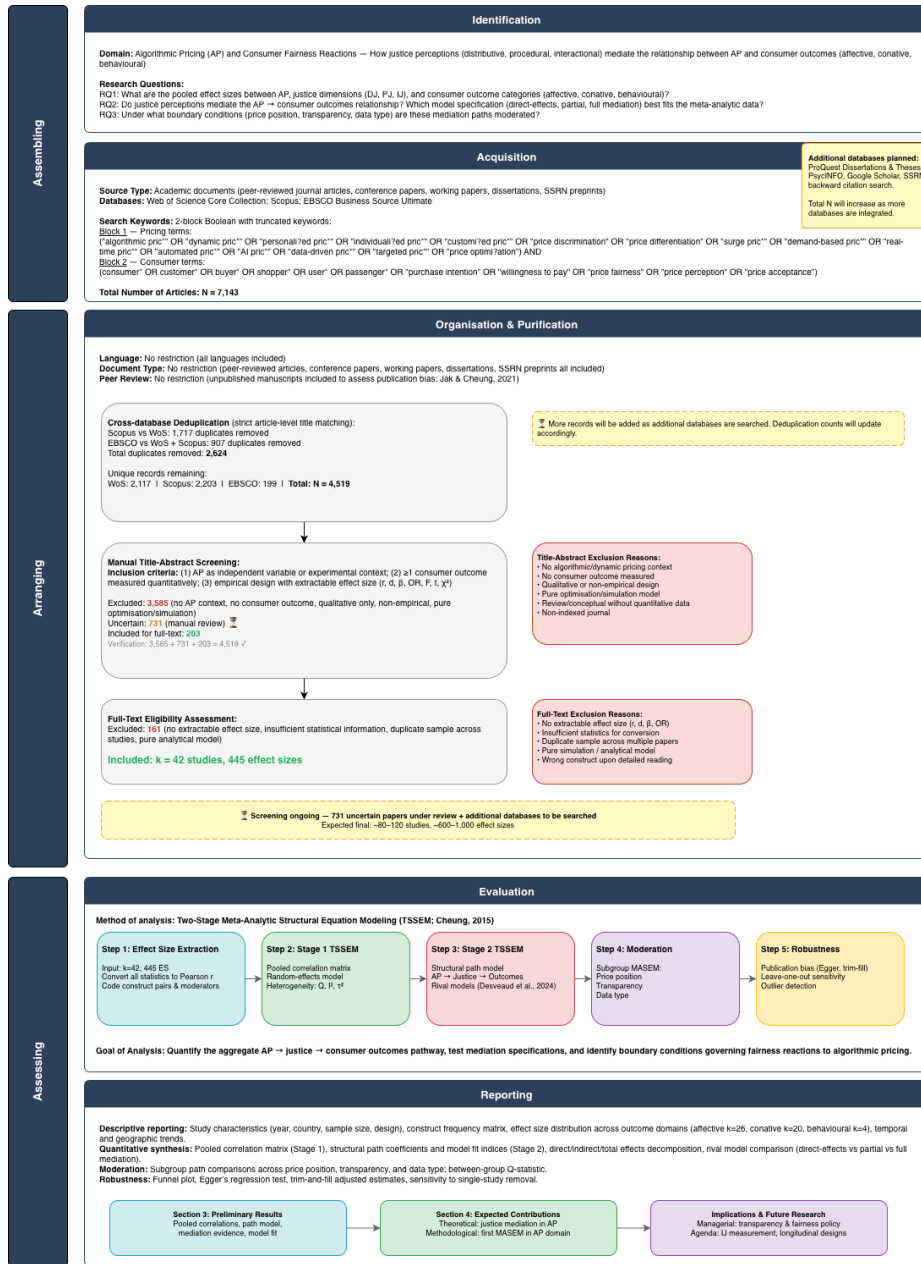
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Appendix A. PRISMA Paper-Selection Flow Chart



Appendix B. Construct Operationalisation (Famarzi-style)

Each construct is documented with its conceptual definition, its operationalisation in primary studies (with a sample item), the dominant scale-anchor source, and k papers in our corpus that report the construct. Style follows Famarzi & Bhattacharya (2024 *JM*) and Desveaud, Mandler & Eisend (2024 *JBR*) meta-analytic appendix conventions.

Construct	Conceptual Definition	Operationalisation in Primary Studies (sample item)	Scale Anchor	k Papers
Independent variable — algorithmic-pricing exposure				
AP_MECH	Exposure to an algorithmically-set price (DP or PP).	“The price you saw was set by an algorithm that adjusts in real time based on demand and customer characteristics.”	Vomberg et al. 2024 <i>IJRM</i> (manip.); Garbarino & Maxwell 2010 <i>JBR</i> (measure).	80
Cognitive antecedent (Layer 1)				
COG	Cognitive appraisal of the algorithmic stimulus — trust, suspicion, perceived value, betrayal-suspicion.	e.g., “I trust this seller / The price feels suspicious / The price reflects what the product is worth.” (7-pt Likert)	Ferguson et al. 2014 <i>JR</i> ; Grégoire et al. 2009 <i>JM</i> ; Gefen & Straub 2003 <i>MISQ</i> .	51
Justice mediators (Layer 2)				
DJ	Perception that the price outcome is equitable relative to comparison standards.	“The price I paid is fair / reasonable / acceptable compared to others.” (3-item, 7-pt Likert)	Campbell 1999 <i>JMR</i> ; Xia, Monroe & Cox 2004 <i>JM</i> .	28
PJ	Perception that the pricing process was transparent, consistent, and legitimate.	“The way the price was determined is fair / acceptable.” (3-item, 7-pt Likert)	Bolton, Warlop & Alba 2003 <i>JCR</i> ; Leventhal 1980.	16
OF	Aggregate fairness judgement when DJ and PJ are not separable.	“Overall, the price is fair.” (1- or 3-item, 7-pt Likert; bipolar or unidirectional anchor)	Riquelme 2019 <i>JBR</i> ; Haws & Bearden 2006 <i>JCR</i> .	28
Consumer-reaction outcomes (Layer 3)				
AFF	Emotional reactions (positive: gratitude, satisfaction; negative: anger, worry, betrayal).	e.g., “I feel angry / upset / worried / grateful / satisfied about this price.” (7-pt Likert)	Bougie, Pieters & Zeelenberg 2003 <i>JAMS</i> ; Watson, Clark & Tellegen 1988 <i>PANAS</i> .	34
CON	Behavioural intentions (purchase intent, switching intent, NWOM intent).	e.g., “I would purchase / switch sellers / tell others negatively.” (3-item, 7-pt Likert)	Zeithaml, Berry & Parasuraman 1996 <i>JM</i> .	51
BEH	Observed consumer behaviours (click, purchase event, defection, complaint).	e.g., Click-through rate, observed purchase / non-purchase event, observed defection or complaint.	Field or archival data (no scale).	8
Moderating conditions				
Price Position	Whether the consumer receives a price above	Coded from experimental condition; 3-level categorical	Wang & Krishna 2012 <i>JCP</i> ; Haws & Bearden 2006 <i>JCR</i> .	—

Construct	Conceptual Definition	Operationalisation in Primary Studies (sample item)	Scale Anchor	k Papers
	or below a reference point.	(Advantaged / Disadvantaged / Control).		
Transparency	Whether the algorithmic basis of the pricing decision is disclosed.	Coded from experimental manipulation; binary disclosed vs. concealed.	Bhattarai et al. 2023; Bambauer-Sachse & Young 2024 JSR.	—
Data Type	Category of personal data the algorithm uses to set the individualised price.	Coded from study description; categorical (Demographic / Behavioural / Biometric).	Hufnagel et al. 2022; Yan et al. 2025.	—
Cultural Context	Country-level cultural setting of the primary study sample.	Hofstede dimensions (PDI, IDV, UAI, MAS, LTO, IVR); Inglehart-Welzel cluster.	Hofstede 2001; Inglehart & Welzel 2010.	—
Methodological Design	Study-level design attributes (random assignment, sample composition, setting).	Random assignment (Y/N), sample age SD, sample size, sample recruitment platform, study setting.	Faramarzi & Bhattacharya 2024 JM; Barari et al. 2025 JAMS.	—
Publication-Quality Tier	Outlet ranking of the primary study (publication-bias proxy).	ESCP Tier (Alpha / AFT / A / B / C / D); FT50 (Y/N); SJR Quartile; ABS ranking.	Faramarzi & Bhattacharya 2024 JM; Hunter & Schmidt 2004.	—