

Bridging Model Sophistication and Managerial Adoption: A Structured Review of Operations Research in FMCG Supply Chain Optimization

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Abstract

Operations research (OR) has long supported supply chain decisions for fast moving consumer goods (FMCG), a sector marked by thin margins, short shelf lives, demand that swings with promotions and highly fragmented retail. This review examines whether OR models capture these features and whether richer models reach practice. We analyse 22 peer reviewed applications published between 1994 and 2024, coding each model against seven defining characteristics of FMCG to form an FMCG Specificity Index, and against a four level scale of adoption evidence. Nineteen of the 22 models extend the classical transportation problem. Mean specificity is low, at 2.09 out of 7: promotions are modelled in one study and demand uncertainty in four. Adoption evidence is not significantly related to specificity (Spearman $\rho = -0.21$, $p = 0.36$) but tends to decline as solution methods grow more complex ($\rho = -0.37$, $p = 0.12$). All five implemented models rely on exact methods or constructive heuristics, whereas none of the six metaheuristic models reports implementation. We therefore propose simplicity preserving specificity as a design principle and demonstrate it with real promotion data from a US grocery retailer. The resulting FMCG Fractile Method can be applied in a spreadsheet, matches the optimal stochastic plan to within 0.005 percent of expected cost, and reduces expected cost by 13 to 57 percent relative to planning that ignores promotions. The review closes with a research agenda and a reporting checklist for FMCG optimisation studies.

Keywords: fast moving consumer goods; supply chain optimisation; operations research; transportation problem; vehicle routing; promotions; newsvendor; model adoption

1. Introduction

Fast moving consumer goods (FMCG), such as packaged food, beverages, dairy and personal care products, sell in high volumes at low prices and thin margins. Their supply chains face short shelf lives, promotional demand swings, wide product ranges and delivery to many outlets, from retail chains to small independent stores. Thin margins make distribution cost and availability decisive, so FMCG is a natural field for operations research (OR).

OR has served the field since the transportation problem (Hitchcock, 1941) and the truck dispatching problem (Dantzig & Ramser, 1959). Documented applications at Procter & Gamble, Kellogg and Coca-Cola Enterprises report savings from millions to hundreds of millions of US dollars a year (Brown et al., 2001; Camm et al., 1997; Kant et al., 2008). Recent academic models add perishability, uncertainty and emissions, solved with increasingly sophisticated metaheuristics.

Two questions remain unexamined. Do models represent what distinguishes FMCG from generic freight (*specificity*), and do richer models reach practice (*adoption*)? OR scholars have long warned of a gap between models and managers (Ackoff, 1979; Little, 1970), but, to our knowledge, it has not been

measured for FMCG. Adjacent reviews classify models by technique or product, for example in dairy (Malik et al., 2022), rather than by their fit with the FMCG setting. We therefore ask:

RQ1. What common structure underlies OR models of FMCG supply chains?

RQ2. How far do these models represent defining FMCG characteristics?

RQ3. How does the way specificity is represented relate to evidence of adoption?

The paper contributes (i) a transparent coding framework, the FMCG Specificity Index (FSI) and Adoption Evidence Level (AEL); (ii) evidence of a shared model kernel and a demand side specificity gap; (iii) evidence that adoption is associated with tractability rather than specificity; (iv) the design principle of *simplicity preserving specificity*; and (v) the FMCG Fractile Method (FF Method), a new spreadsheet rule for promotional dispatch that, on real promotion data, matches the full stochastic transportation model.

2. Review Method

2.1 Search and selection

We searched ScienceDirect, SpringerLink, Taylor & Francis Online, Emerald Insight, INFORMS PubsOn-line, IEEE Xplore, MDPI and RePEc/IDEAS, combining product terms (“FMCG”, “fast moving consumer goods”, “dairy”, “perishable food”) with problem terms (“transportation problem”, “vehicle routing”, “distribution network”, “production and distribution”, “inventory routing”, “cross docking”). Eligible studies were peer reviewed journal articles or conference papers that formulated a quantitative OR model for an FMCG setting using real or realistic data. From these we drew a purposive, maximum variation sample of 22 studies covering three planning levels, four regions, three decades, and both practice reports and academic modelling. The sample is designed for contrast, not completeness.

2.2 Coding framework

Each model was coded against seven characteristics (Table 1), drawn from standard descriptions of FMCG and the motivations stated in the studies. Promotions are included as a dominant source of FMCG demand variation (Blattberg et al., 1995). A characteristic scores 1 only if it enters the model as a parameter, variable, constraint or objective; discussion or sensitivity analysis alone scores 0. The FSI is the sum (0 to 7).

Table 1. Defining FMCG characteristics used for coding

Code	Characteristic	Scored 1 when the model includes
S1	Perishability	Shelf life, freshness, product age or a maximum pickup to delivery time
S2	Demand uncertainty	Stochastic, fuzzy, possibilistic or scenario based demand
S3	Promotional demand	Promotional uplift, or promotion linked stock or capacity rules
S4	Product variety	Several products or SKUs with distinct attributes
S5	Multiechelon structure	Two or more distribution tiers optimised jointly
S6	Multistop routing	Frequent multistop pickup or delivery routes
S7	Retail channel structure	Retailer DCs, order size regimes, store types or outlet level rules

Adoption evidence has four levels: AEL 0, illustrative data; AEL 1, real data with no reported implementation; AEL 2, implemented or used for decision support; AEL 3, implemented with reported savings. Solution methods were classed as exact linear/network, exact mixed integer, constructive heuristic, metaheuristic or evaluative (cost or simulation) models. Associations were tested with Spearman rank correlation.

To assess reliability, every study was coded twice, independently, against the written rubric, using the full text where accessible and the published abstract otherwise. The two codings agreed on 145 of

154 characteristic codes (94.2%, Cohen's $\kappa = 0.86$) and on 21 of 22 adoption levels (linearly weighted $\kappa = 0.95$). The ten disagreements were resolved by returning to the source text; the reconciled codes are used throughout. Claude (Anthropic) assisted with drafting, data cleaning, formulation and a second coding pass.

3. Summary of the Literature

The studies form four streams. Codes appear in brackets as (FSI, AEL).

3.1 Network design and sourcing

Camm et al. (1997) restructured Procter & Gamble's North American supply using integer programming for location, network flow for sourcing, and a geographical information system through which managers tested options. P&G cut its North American plants by almost 20% and saved over US\$200 million a year before tax (1, 3). Wouda et al. (2002) used mixed integer linear programming (MILP) to redesign Nutricia's Hungarian dairy network, including interplant transfers; the model became the group's decision support tool (1, 2).

Kellner et al. (2013) optimised a German FMCG manufacturer's distribution centres and varied five drivers, including retailer order sizes. Single changes could shift the optimum, but combined changes largely offset each other (3, 1). Mishra et al. (2024) modelled India's move to consolidated warehouses after the Goods and Services Tax (GST) with multiple product lines and truck types, finding that freight rates, not rent, drive total cost (2, 1). Jayarathna et al. (2022) located a central warehouse for a Sri Lankan FMCG firm serving 5,483 clients and redesigned its routes, reporting a 34.2% cost reduction (1, 1). Jackson et al. (2023) combined a centre of gravity model with a MILP solved in Gurobi to allocate export volumes and choose inland transport modes for a multinational FMCG firm shipping from 13 North American plants to customers in 37 Latin American countries; synchromodal planning cut total cost by 9% (1, 1).

3.2 Integrated production, inventory and distribution

Kellogg's planning system is the most mature tactical model (Brown et al., 2001). It is a multiperiod linear programme covering about 80 cereal products and over 600 SKUs across five plants and seven distribution centres. Promotions raise safety stock requirements over promotional weeks, and a sliding window bars production more than five months before demand. Operational use saved an estimated US\$4.5 million in 1995, and a tactical consolidation study projected US\$35 million to US\$40 million a year (4, 3).

Amorim et al. (2012) traded cost against delivered freshness in multiobjective MILPs and showed that integration benefits depend on the freshness required (2, 0). Abdallah and El-Beheiry (2022) modelled a multinational's three echelon Egyptian network of 120 distribution centres as a mixed integer quadratic programme solved in LINGO; vendor managed inventory was consistently the cheapest policy (1, 1). Dehghani Jeshvaghani et al. (2023) integrated production, inventory, routing and cross docking for a real FMCG supply chain under uncertain demand, using robust possibilistic programming and metaheuristics (4, 1). Olanrele et al. (2023) combined linear programming with Monte Carlo demand simulation to plan annual production for a sanitary pad manufacturer, raising expected profit by 2.06% and cutting variable cost by 7.65% (2, 1).

Three evaluative studies compare distribution or information strategies rather than optimise flows. For an FMCG supplier and a French retailer, Benrqya (2019) compared cross docking with traditional warehousing through a cost model (2, 1), and Benrqya et al. (2020) used an order up to inventory model to show that the best strategy depends on product characteristics (4, 1). Ali et al. (2020) simulated a four tier, three product FMCG chain in Arena with stochastic demand and lead times, finding that centralised information sharing reduces but cannot eliminate the bullwhip effect (3, 1).

3.3 Routing and last mile distribution

Sankaran and Ubgade (1994) built heuristic routing support for Etah Dairy, where each tanker's pickup to delivery time must stay within a seasonal limit; it was implemented with projected benefits of Rs. 1 million a year (2, 2). At Coca-Cola Enterprises, over 300 dispatchers plan about 10,000 trucks daily with savings based routing software, which saves US\$45 million a year after a gradual rollout (Kant et al., 2008; 1, 3).

Academic routing work emphasises algorithms. Amorim and Almada-Lobo (2014) separated cost from freshness in a multiobjective routing problem with time windows (2, 0). Jabir et al. (2022) designed routes that minimise distance, emissions or a balance of the two for an Indian milk cooperative using an ant colony and neighbourhood search hybrid (1, 1). Kumar et al. (2024) used GIS route optimisation to cut cost and dead kilometres for Sanchi dairy in Bhopal (1, 1).

3.4 Sustainability and resilience

Govindan et al. (2014) formulated a two echelon location routing problem for perishable food that trades cost against emissions, solved by a hybrid of particle swarm and neighbourhood search (3, 0). Validi et al. (2014) designed a low emission distribution network for Irish milk with genetic algorithm optimisers (1, 1). Asgharizadeh et al. (2023) modelled FMCG home distribution during COVID-19 as a multiproduct location routing problem balancing cost and freshness; replacing vehicle routing with direct allocation raised network cost by 15.14% while improving freshness by 6.12% (4, 1).

4. Findings Across Studies

4.1 One kernel, many layers (RQ1)

Despite different labels, 19 of the 22 models extend one kernel, the classical transportation problem. Plants i with capacity a_i ship x_{ij} units to destinations j with demand d_j at unit cost c_{ij} :

$$\min \sum_i \sum_j c_{ij} x_{ij} \quad \text{s.t.} \quad \sum_j x_{ij} \leq a_i \quad \forall i, \quad \sum_i x_{ij} = d_j \quad \forall j, \quad x_{ij} \geq 0. \quad (1)$$

Each model adds some of seven layers: location, time and inventory, routing, products, freshness, uncertainty and extra objectives. The exceptions are the three evaluative studies (Ali et al., 2020; Benrqya, 2019; Benrqya et al., 2020). One layer changes the solution method: all nine studies with routing rely on heuristics or metaheuristics at realistic scale, with exact methods only for small instances (Amorim & Almada-Lobo, 2014; Jabir et al., 2022). By contrast, eight of the ten optimisation models without routing use standard exact solvers; the exceptions are Kellner et al. (2013), who add a Lagrangian heuristic, and Validi et al. (2014), who use genetic algorithms. Routing is where FMCG models leave exact optimisation.

4.2 The specificity gap (RQ2)

Mean FSI is 2.09 of 7 (median 2), and no study exceeds 4. Supply side structure is well covered; the demand side and channel features that most distinguish FMCG are rarely modelled (Table 2).

The gap is sharpest where studies cite FMCG features as motivation and then assume them away. Jayarathna et al. (2022) note that demand varies with social, cultural, seasonal and environmental factors, yet their model allows no demand fluctuation and aggregates 47 SKUs into one volume. Asgharizadeh et al. (2023) assume certain demand and leave uncertainty to future work, and Jackson et al. (2023) note that their deterministic MILP “has many limitations in light of real-world uncertainty”. Only Kellogg's system represents promotions, and only two optimisation models treat demand as uncertain (Dehghani Jeshvaghani et al., 2023; Olanrele et al., 2023).

Table 2. Share of the 22 studies that model each characteristic

Characteristic	Studies	Share
S5 Multiechelon structure	12	55%
S4 Product variety	11	50%
S6 Multistop routing	9	41%
S1 Perishability	6	27%
S2 Demand uncertainty	4	18%
S7 Retail channel structure	3	14%
S3 Promotional demand	1	5%

4.3 Adoption follows tractability more than specificity (RQ3)

Five studies report implementation (AEL 2 or 3), and specificity does not set them apart ($\rho = -0.21$, $p = 0.36$, $n = 22$). Solution method complexity shows a negative but weaker association: among the 19 optimisation models, adoption evidence tends to fall as methods move from linear programming through mixed integer programming and heuristics to metaheuristics ($\rho = -0.37$, $p = 0.12$). The descriptive pattern is sharper. All five adopted models use exact programming or constructive heuristics, and none of the six metaheuristic models reports implementation (Table 3).

Table 3. Studies by adoption evidence and solution method

AEL	Exact LP / network	Exact MILP / MIQP	Constructive heuristic	Metaheuristic	Evaluative model
3	Brown et al. (2001)	Camm et al. (1997)	Kant et al. (2008)		
2		Wouda et al. (2002)	Sankaran & Ubgade (1994)		
1	Olanrele et al. (2023)	Kellner et al. (2013); Abdallah & El-Beheiry (2022); Jackson et al. (2023); Mishra et al. (2024)	Jayarathna et al. (2022); Kumar et al. (2024)	Validi et al. (2014); Jabir et al. (2022); Dehghani Jeshvaghani et al. (2023); Asgharizadeh et al. (2023)	Ali et al. (2020); Benrqya (2019); Benrqya et al. (2020)
0		Amorim et al. (2012)		Govindan et al. (2014); Amorim & Almada-Lobo (2014)	

Note. AEL 3 = implemented with reported savings; 2 = implemented or used; 1 = real data, no implementation reported; 0 = illustrative data.

Kellogg is the clearest case. Its system shares the highest specificity in the sample (FSI 4) yet remains a linear programme, because promotions and shelf life enter as safety stock rules and a sliding production window. The three academic optimisation models that reach FSI 3 or 4 through new structure (Govindan et al., 2014; Dehghani Jeshvaghani et al., 2023; Asgharizadeh et al., 2023) all need metaheuristics and report no adoption. The only other optimisation model at this level, Kellner et al. (2013), reaches FSI 3 through product variety and retail channel structure within an exact location model, but it too reports no implementation. Olanrele et al. (2023) show the simpler route for uncertainty, wrapping Monte Carlo demand scenarios around a linear programme, although they too report no implementation.

Two confounds temper this reading. Four of the five adopted studies appeared in *Interfaces*, which requires implementation, and all five date from 1994 to 2008, while the metaheuristic models in the sample date from 2014 onwards. The pattern is suggestive rather than causal, but the absence of any implementation report after 2008 is itself a finding.

5. Discussion

Little (1970) argued that managers use models that are simple, robust, easy to control, adaptive, complete on important issues and easy to communicate with. The adopted models fit that description. Kellogg's linear programme ran inside routine planning for over a decade; Coca-Cola Enterprises moved to routing software gradually from existing practice; P&G's managers adjusted optimised networks through maps they could read. Each traded some completeness for control and communication.

Academic models make the opposite trade, gaining completeness through new structure such as fuzzy demand, cross dock operations and multiple objectives. Each addition pushes the model toward metaheuristics, whose results carry no optimality guarantee, depend on tuning and are hard for planners to audit. Three mechanisms likely widen the gap: *auditability* (a planner can trace why an LP moved a truckload, but not why a swarm algorithm did), *data burden* (promotion calendars, shelf life rules and SKU dimensions sit in separate systems) and *incentives* (academic venues reward methodological novelty, while implementation is reported mainly in practice outlets).

Kellogg shows that specificity and tractability need not conflict. We call this *simplicity preserving specificity*: encoding FMCG features in forms that keep the model within the reach of standard exact solvers. Four devices serve this purpose: **parameter adjustment** (promotional weeks raise safety stock or demand), **preprocessing** (removing arcs or periods that would breach shelf life, as Kellogg's sliding window does), **scenario expansion** (a few demand scenarios keep the model linear) and **linear penalties** (freshness loss or emissions priced in the objective). A fifth device, **closed form decision rules** derived from the model's structure, is developed in Section 6. Two propositions follow.

P1. Models that encode specificity through these devices will show higher adoption than equally specific models that need metaheuristics.

P2. Most of the value of an FMCG characteristic is captured by its simplest representation.

6. Illustration: A Transportation Model with Promotional Demand

We extend the kernel with the least covered characteristic, promotional demand, to test P2. The promotional uplift is estimated from real transaction data: the 84.51° Complete Journey data set, which records one year of grocery purchases by 2,469 households at a US retailer, together with the weeks in which each product was featured in the store's promotional mailer (84.51°, n.d.; Boehmke & Mortimer, 2025). For every product with a baseline of at least 20 units a week, uplift is the product's sales in a featured week divided by its median sales in weeks without a feature. Across 767 featured product weeks for 75 products, the median uplift is 1.88, but the distribution is highly skewed: the lower, middle and upper thirds average 1.00, 1.93 and 4.90. These three levels, each with probability 1/3, define the promotion scenarios.

The network is stylised because lane level freight rates and plant capacities of real firms are not public. Three plants with capacities of 20, 15 and 25 truckloads a month supply four depots with baseline demand of 5, 8, 7 and 8 truckloads, at freight costs of INR 8,000 to 70,000 per truckload. The promoted product line is sold through depot D4. Dispatches are fixed before the promotion starts, so unmet demand is lost at margin p and surplus stock costs h per truckload. The base case uses $p = \text{INR } 150,000$ and $h = \text{INR } 20,000$, and both are varied in a sensitivity analysis.

The stochastic plan solves a two stage stochastic transportation problem with simple recourse (Williams, 1963), where scenario s has probability π_s and demand d_{js} , and u_{js} and e_{js} are shortage and surplus:

$$\min \sum_i \sum_j c_{ij} x_{ij} + \sum_s \pi_s \sum_j (p u_{js} + h e_{js}) \text{ s.t. } \sum_j x_{ij} \leq a_i \forall i, \sum_i x_{ij} + u_{js} - e_{js} = d_{js} \forall j, s, x, u, e \geq 0. \quad (2)$$

Each plan in Table 4 is evaluated against all three scenarios; models were solved with the HiGHS solver in Python (SciPy).

Table 4. Expected monthly cost of dispatch plans, base case (INR thousand)

Plan	To D4	Freight	Shortage & surplus	Expected total	Lost truckloads
Baseline (ignores promotion)	8.0	519.0	1,929.0	2,448.0	12.86
Expected value (mean uplift)	20.9	706.2	1,037.1	1,743.3	6.10
Stochastic (plans for promotion)	32.0	929.0	628.7	1,557.7	2.39
Perfect information (bound)	varies			782.0	0.00

In the base case, the expected value plan, which is the ordinary transportation model with one demand parameter raised, cuts expected cost by 28.8% against the baseline plan. Modelling the uncertainty explicitly cuts it by 36.4%, a value of the stochastic solution (Birge, 1982) of INR 185,700, or 10.7%. The simplest representation therefore captures 79% of the total gain. Across nine combinations of $p \in \{75, 150, 300\}$ and $h \in \{10, 20, 40\}$ (INR thousand), the stochastic plan lowers expected cost by 13% to 68%, and the expected value plan captures between 39% and 97% of that gain (median 74%). P2 therefore holds in eight of the nine settings. The exception, and the settings with high margins, show that real promotion outcomes are skewed enough for explicit uncertainty modelling to add substantial value. Even so, the stochastic model grows only from 12 variables and 7 constraints to 36 and 15, and remains a linear programme that standard solvers handle exactly.

6.1 A new decision rule: the FMCG Fractile Method

The expected value plan is simple but not reliable: across the nine settings its cost exceeds the optimum by up to 35%. We therefore propose a rule that is equally simple to apply but exact in this setting, which we call the *FMCG Fractile Method* (FF Method). It extends the critical fractile of the classical newsvendor problem (Khouja, 1999) by pricing each additional truckload at its own marginal freight cost, taken from the transportation kernel.

The rule needs two inputs a planner already has. The first is the empirical distribution F of promoted demand, equal to base demand multiplied by historical uplift. The second is the *incremental freight curve*: the extra freight cost m_k of the k th truckload sent to the promoted depot once all other depots are served. The curve is read from the ordinary transportation model or from the lane rate card, because each extra truckload moves on the cheapest lane that still has spare capacity. The planner ships the k th truckload if and only if

$$F(k) \leq \frac{p - m_k}{p + h}, \quad (3)$$

that is, while the probability that promoted demand falls below k truckloads does not exceed that truckload's own critical fractile. In our network the curve has three steps (INR 10,000, 20,000 and 42,000 per truckload), so the rule reduces to three percentile lookups in a spreadsheet.

When only one depot is promoted and the others face known demand, the stochastic transportation problem separates into a newsvendor problem with a piecewise linear convex ordering cost, and the rule is optimal. Numerically, on all 767 empirical uplift scenarios and all nine (p, h) settings, the FF Method plan comes within 0.005% of the optimal expected cost; the small residual arises only because the rule was evaluated in steps of a quarter truckload (Table 5). An independent brute force search over shipment quantities reproduced every optimum. The rule captures at least 99.99% of the achievable saving, which ranges from 13% to 57% of the baseline cost, whereas the expected value plan exceeds the optimum by up to 35%. A simpler critical fractile that prices every truckload at the cheapest lane performs far worse, exceeding the optimum by up to 69%, which shows that the incremental freight curve is the essential

ingredient.

Table 5. FF Method versus the optimal stochastic plan (767 real uplift scenarios)

p (INR thousand)	h	Truckloads to D4		Cost above optimum		Optimal saving vs baseline
		FF Method	Optimum	FF Method	Expected value	
75	10	20.25	20.40	0.0005%	0.01%	19.1%
75	20	17.00	17.14	0.0027%	1.22%	16.3%
75	40	15.00	15.00	0.0000%	5.75%	12.7%
150	10	32.00	32.00	0.0000%	10.90%	39.5%
150	20	30.25	30.26	0.0002%	5.25%	34.0%
150	40	22.75	22.99	0.0050%	0.35%	26.1%
300	10	36.75	36.80	0.0004%	35.32%	57.2%
300	20	34.75	34.93	0.0014%	27.17%	53.5%
300	40	32.00	32.00	0.0000%	16.46%	46.9%

Note. Truckloads are continuous because the model is a linear programme. The baseline plan ships the base demand and ignores the promotion. All 767 observed uplifts are treated as equally likely, so optimal plans differ slightly from the three scenario case in Table 4.

The FF Method is the clearest instance of simplicity preserving specificity in this paper: it represents promotion uncertainty fully, yet a planner can compute and audit it without an optimisation solver. Its exactness relies on a single promoted depot. When several regions are promoted at once they compete for plant capacity, and the rule becomes a heuristic whose accuracy remains to be tested.

7. Research Agenda and Reporting Checklist

The gaps suggest five priorities: (1) **promotions**, testing scenario LPs against adjusted forecasts on real promotion histories; (2) **demand uncertainty**, identifying linear representations that keep most of the value of stochastic or robust models; (3) **retail channel structure**, modelling traditional trade features such as small drops, restricted access and cash collection at independent stores, especially in markets like India; (4) **adoption as an outcome**, testing P1 and P2 through field studies with planners; and (5) **implementation evidence since 2008**, through follow up studies of deployed models.

To make studies comparable, FMCG OR papers should report: which FMCG characteristics are modelled or assumed away; data source and instance size; baseline practice and savings in money terms; solver, runtime and optimality gap; validation approach; and implementation status on the AEL scale.

8. Conclusion

This review examined 22 OR applications to FMCG supply chains. The field rests on one transportation kernel extended layer by layer, with routing marking the move from exact to heuristic methods. Models capture supply side structure well but seldom the demand side features that define FMCG. Adoption evidence appears to follow tractability rather than specificity, and the one highly specific, widely used model, Kellogg's, encodes FMCG features through simple linear devices. Researchers should therefore pursue *simplicity preserving specificity*, of which the FMCG Fractile Method (FF Method), a spreadsheet rule that matches the optimal stochastic plan, is a worked example; practitioners can capture much of the available value with simple extensions of familiar models.

Limitations. The sample is purposive; a systematic Scopus or Web of Science search could test the patterns at scale. The FSI weights characteristics equally and records presence, not depth. Adoption evidence depends on what authors report. In the illustration, promotional uplift comes from real transaction data from a US grocery retailer, but the network and cost parameters are stylised, and the FF Method is proven exact only for a single promoted depot.

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Data availability. The Complete Journey data are publicly available from 84.51° and in the R package complete-journey. The coding of the 22 studies and the Python scripts that reproduce Tables 4 and 5 are available from the authors on request.

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