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Bidding for B2B or B2G tenders: toward the adoption of pricing models in practice

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Abstract

This study investigates the lack of adoption of pricing models for tenders in business-to-business (B2B) and business-to-government (B2G) markets. We aim to identify the gaps between research and practice and propose a future research agenda to bridge these gaps. Our study contributes in three ways: First, we outline how our research agenda can influence the adoption of pricing models across specific practitioner roles in tendering. Second, we introduce systematic science mapping (SSM) as a novel methodology for literature reviews. SSM combines a systematic review and science mapping in a multi-stage, mixed-methods research design. We chart the evolution of 1042 research publications from 1956 to 2022 into three thematic areas. Our review of 163 gray literature publications reveals seven schools of thought on tender price modeling and the causes of theory-to-practice gaps. Finally, we introduce a new metric, the mapping factor (MAPF), as a robustness indicator for systematic literature reviews.

Keywords Competitive bidding · Tendering · B2B pricing · Systematic science mapping (SSM) · Systematic review · Mapping factor (MAPF)

JEL Classification C63 · D44 · L11 · L74 · L81 · M21

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1 Introduction

Many consumers could relate to a competitive bidding situation from personal experiences with internet web sites such as eBay, Gumtree, Facebook Marketplace, Craigslist, OfferUp, Mercari, or even charity auctions. This research does not concern consumer-to-consumer (C2C) or business-to-consumer (B2C) bidding. The focus here is on markets in which the product, service, or bundled solution is delivered in business-to-business (B2B) or business-to-government (B2G) markets. For brevity, we include B2G when we refer to B2B in this study.

A definition of competitive bidding for when the bid-taker is *procuring*[1] a product or service is provided by Ballesteros-Pérez et al. (2013) as "a transparent procurement method in which bids from competing contractors, suppliers, or vendors are invited by openly advertising the scope, specifications, and terms and conditions of the proposed contract, as well as the criteria by which the bids will be evaluated." The evaluation criteria have become ever more important with the World Trade Organization's emerging move away from selecting the bid with the lowest price, which dominated bid modeling research since the previous century (Friedman 1956; Gates 1967; Oo et al. 2007; Rothkopf and Harstad 1994; Takano et al. 2018). In a step toward "sustainable public procurement" (Džupka et al. 2020), the European government procurement now includes criteria for the "most economically advantageous tender" (MEAT). Here, the winning bid is determined through evaluation against published award criteria to allow for a balance between price and quality (Stake 2017). Nevertheless, the lowest price remains the dominant selection criterion in most procurements today (Loosemore and Richard 2015; Semaan and Salem 2017; Venkataraman and Petersen 2022).

When the bid-taker is *selling* a contract, competitive bidding has been used to auction telecommunications spectrum, government securities, initial public offerings (IPOs), corporate takeovers, airport slots, offshore oil leases, distribution of electrical generation, and emissions credits (Güçbilmez and Briain 2021; Whitford 2007; Woodward 2015). In auction theory, this competitive bidding mode is known as a forward auction (Chen et al. 2022). In such selling scenarios, the winning bid typically is the highest, but *selling and buying scenarios* both lead to the same research conclusions with an almost perfect correspondence in competitive bidding results (Skitmore 2014; Harstad and Pekeč 2008; Ballesteros-Pérez et al. 2012).

This research focuses on the *pricing* of large contracts where the bid-takers are public or industry procurement departments. In auction-theoretic terms, this mode of competitive bidding is referred to as a "reverse auction," "sealed bid auction," or, more recently, as a "buyer-determined auction" (Engelbrecht-Wiggans et al. 2007; Haruvy and Jap 2012). In industry practice, these auction mechanisms are known as "tendering", although the academic literature treats the term synonymously with "competitive bidding" or "competitive tendering" (Durugbo and Al-Balushi 2022). Tendering can take on various forms (Holma et al. 2020; Wood and Fitzalan 2015):

[1] The terms "procurement", "purchasing", "buying", or "sourcing" are often used interchangeably in the literature (Hofmann et al. 2020).

(1) any bidder can respond to open tenders; (2) bidders are paired down to a short-list in multi-stage tenders; or (3) some individual bidders may be invited. Specific "RFx" procurement methods exist for tenders, whereby "RF" denotes "request for" and "x" can take on "tender," "proposal," "quotation," or "information" (Matel et al. 2019; Zahid et al. 2021). The final price is often negotiated in a process leading to a bidder's best-and-final offer (BAFO), which summarizes any differences from the original bid (Haruvy and Jap 2022; Smith 2017; Venkataraman and Petersen 2022).

For tender pricing, practitioners need to understand several dimensions, such as (Brindley et al. 2017; Gartner Group 2022; Pickar and Feely 2017; Shipley 2022):

- What are the main decision factors on the bidding and procurement sides?
- Why should the cost of tendering be incurred versus making a "no-bid" decision?
- What analytical methods can help bidders predict their competitors' prices and non-price features?
- How much competitive intelligence do such analytics demand?
- How reliable are the bidders' cost estimates?
- What is the optimal tendering strategy over time?

Since the 1950s, scientists have developed pricing models to assist bidders in these questions (Friedman 1956; Vickrey 1961; Gates 1967; Rothkopf 2001; Harstad and Pekeč 2008; Kingsman and Mercer 1997). Other pricing models took procurement or regulatory vantage points, such as procurement policies or collusion prevention (Herrmann 2000). However, very few such models have been embraced and implemented in practice (Asgari et al. 2016; Ballesteros-Pérez et al. 2016; Urquhart and Whyte 2018; Skitmore 2008; Kienzler and Kowalkowski 2017). In those few implementations, tendered pricing models have either been deployed as an *incremental* input into the sales process (including the decision to bid or not) or more recently *transformed* the bid process toward "price-to-win" strategies in an interplay between competitive price predictions and cost engineering (Brindley et al. 2017; Newnes et al. 2014b; O'Guin 2017; Pickar and Feely 2017; Urquhart et al. 2017).

From a microeconomic perspective, these scarce implementations are a missed opportunity to improve a bidder's chances of winning contracts and increase profit margins and revenues. A simulation of these benefits from primary data by Herrmann (2019) demonstrated a potential for a 400% improvement in the ratio of won versus lost bids, an 86% increase in the profit margin, and a 76% revenue growth to USD 210 million.

At a macroeconomic scale, the lack of pricing model adoption in tendering practice is a missed opportunity for capturing value as the World Bank estimated the size of the global B2G market in 2018 at USD 11 trillion or 12% of the gross domestic product, GDP (Bosio and Djankov 2020). Another estimate for the same year by the Open Contracting Partnership and Spend Network was USD 13 trillion for B2G (Open Contracting Partnership 2020). Mastercard sized the global business payments market for B2G and B2B combined to exceed USD 100 trillion in the same year (Mastercard 2018), implying that B2B is several times larger than B2G globally (Venkataraman and Petersen 2022). This combined market size demonstrates that competitive bidding—especially for large tendered contracts—significantly impacts the world economy in dollar terms. In a B2G context, tendering is also directly linked with the United Nations' Sustainable Development Goal 12.7 for promoting "public procurement practices that are sustainable, in accordance with national policies and priorities" (Raiden and King 2021).

Therefore, the motivation and objective of this research were to *identify gaps between research and practice in tender price modeling and propose a research agenda for closing those gaps*. This objective is addressed by the following"how", "why", and "what" research questions:

RQ1: *How* has the corpus of tender price modeling evolved thematically?
RQ2: *Why* do theory and practice differ so much?
RQ3: *What* future research agenda can be established for closing identified theory-to-practice gaps?

The structure of this research broadly follows the recommendations by Fisch and Block (2018) for literature reviews in business and management. So far, we have introduced a practitioner-oriented motivation for this research and stated its objective with ensuing research questions. The remainder of this text has been structured around a mixed-methods research design with three stages (Sect. 2). Stage one (Sect. 3) conducts quantitative science mapping to aggregate the corpus into thematic areas from Scopus and addresses RQ1. Stage two (Sect. 4) provides a qualitative literature review, including the gray literature, and categorizes the corpus into schools of thought regarding their methodological differences. RQ2 is addressed by assessing the causes of theory-to-practice gaps for the identified schools. Stage three employs a meta-inference in Sect. 5 by triangulating the results of stages one and two in a holistic integration. From this integration, a future research agenda is presented to deal with RQ3. Finally, conclusions and limitations are summarized in Sects. 6 and 7.

2 Methodology

This research employs a recent *mixed-methods research design* for macro-scale literature reviews, referred to as "*systematic science mapping*" (SSM). The research design has recently been pioneered to develop a taxonomy for artificial intelligence (Herrmann 2022), a research agenda for financial technology or "fintech" (Herrmann and Masawi 2022), reconciliation of ethical principles in business and management (Herrmann 2023a), and a cross-disciplinary review between the fields of responsible innovation and artificial intelligence (Herrmann 2023b). As such, this study addresses the need for methodology-oriented literature reviews in business and management versus the dominance of domain-based reviews (Paul and Criado 2020).

The overarching umbrella component of this design is a *systematic review*, which originates from the field of evidence-based medicine and employs a rigorous and transparent search for assessing and summarizing extant research (Briner and Denyer 2012). Researchers in business and management increasingly rely on systematic reviews because their approach is generally considered superior in scientific rigor compared to traditional reviews (Heyvaert et al. 2013). However, Grayson and Gomersall (2003) note significant differences between the literature in medicine and the social sciences (including business and management), which have "a more diverse literature; [a] greater variety and variability of secondary bibliographical tools; [an] increasing availability of material on the internet; and a less precise terminology." In business research, it is therefore important to use various search strategies for retrieving evidence (Petticrew and Roberts 2008). The mixed-methods research design of this study employs such a requisite range.

SSM is not to be confused or conflated with a 'systematic literature network analysis,' which refers to the multi-method combination of systematic reviews with science mapping in a predominantly quantitative approach (Comerio and Strozzi 2019). Unlike mixed-methods research designs, multi-method designs do not integrate quantitative and qualitative components in a meta-inference (Bazeley 2020). The application of SSM to this study involved a *sequential mixed-methods design* of the literature review in three stages of equal emphasis. Figure 1 depicts a flow chart in an extended PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) notation (Shamseer et al. 2015).

The research design of Fig. 1 can be depicted alternatively in the notation system of Morse (2003) for mixed methods as QUAN ➔ QUAL ➔ meta-inference. Stage one addresses RQ1 through *science mapping* with inclusion and exclusion criteria. This led to 1042 Scopus publications between the years 1956 and 2022 (QUAN). Science mapping is a subfield of *scientometrics*, which provides a decision-making tool for science policy, including research management, such as commissioned reviews and research grants (Hood and Wilson 2001). In the recent decade, science mapping has produced visualization graphs for the evolutionary nature of scientific fields derived from statistical similarity measures and clustering techniques (Santana and Cobo 2020). It is increasingly used in management research (Blümel and Schniedermann 2020) for macro-scale literature reviews of thousands of publications, including entire scientific fields (Mas-Tur et al. 2020). Science mapping offers an alternative to *metanalysis* in primary quantitative studies of the business and management field because such studies often do not report the requisite information to measure their effect size and are inconsistent in their definitions of concepts (Sartal et al. 2021). On the latter point, Grayson and Gomersall (2003) state: "It is extremely unlikely that the social sciences will ever see the equivalent of the highly structured, controlled languages used in medical databases."

The reliance on a single bibliometric database tends to lead to suboptimal results in systematic reviews (Papaioannou et al. 2009; Grayson and Gomersall 2003). Therefore, stage two (literature review, QUAL) extends the systematic review beyond Scopus and conducts a narrative literature review of 163 full texts identified in Google Scholar and the gray literature (QUAL). The use of Google Scholar to increase the coverage of Scopus has been employed by other systematic reviews in business and management (Di Vaio et al. 2022; Shree et al. 2021). The addition of gray literature was conducive to including industry practice and media outside

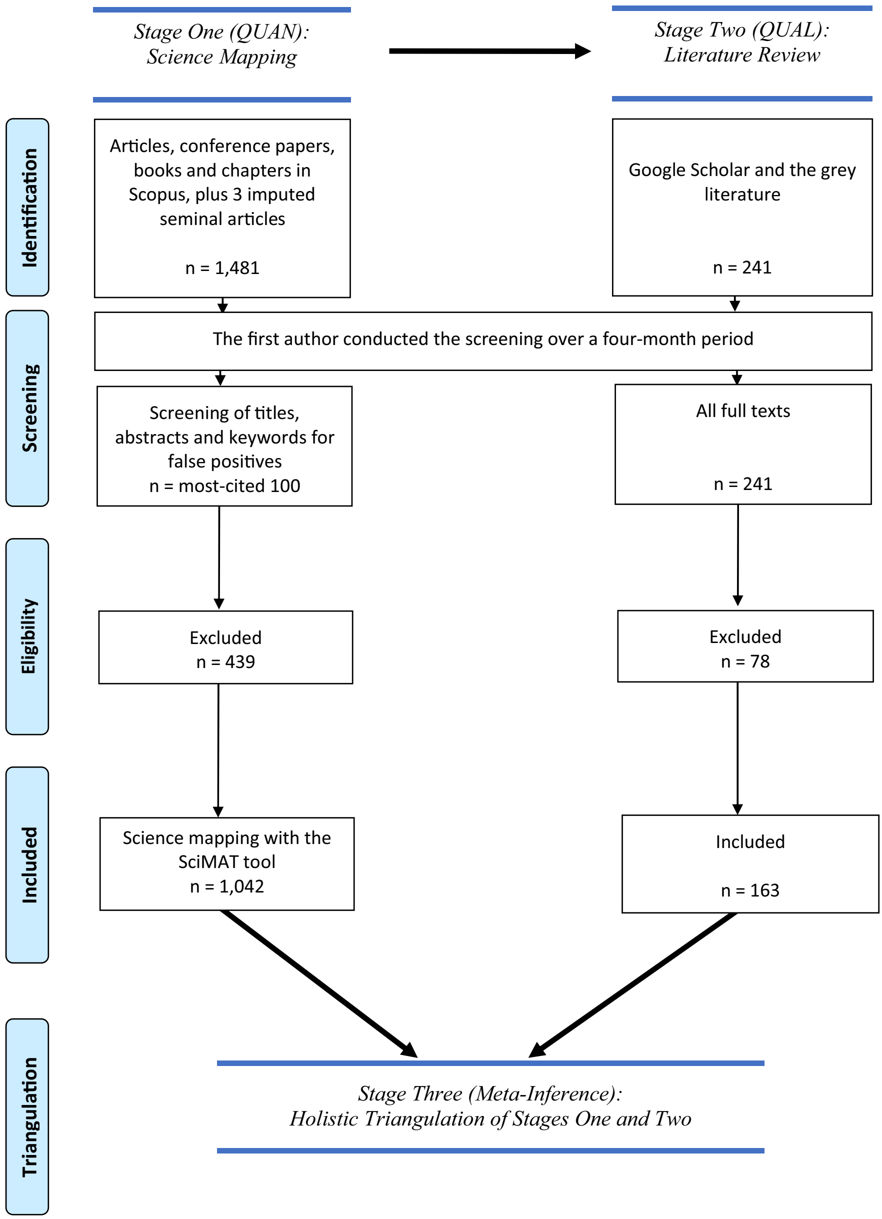

Fig. 1 Research methodology flow chart based on an extended PRISMA notation (source: authors)

academic databases (Adams et al. 2017). This source diversity casts the net wider beyond just Scopus but also provides a diversity of search methods (Petticrew and Roberts 2008) by adding a snowball-based procedure (Wohlin 2014) to the SSM methodology. The literature review added epistemological diversity through a qualitative interpretation of the literature beyond the visualizations offered by science mapping. More holistically, the quantitative approach produced breadth for charting the corpus, and the qualitative approach provided an in-depth assessment and categorization of the corpus, including causes for theory-to-practice gaps. Such an approach for combining breadth and depth is supported by other research (Fisch and Block 2018; Weigend Rodríguez et al. 2020). Stage three's *meta-inference* delivered a holistic triangulation of breadth and depth (Bazeley 2020, 2019).

3 RQ1: Science mapping—thematic evolution of the corpus

Most quantitative, bibliometric research uses Scopus, Web of Science (WoS), or Google Scholar data (Ruiz-Real et al. 2021). The latter is the most extensive database, followed by Scopus; next is WoS, which is the smallest and goes back only to 1972 (Martín-Martín et al. 2021). We searched Scopus, WoS, EBSCO, Emerald, and ProQuest. But none of them consistently indexed the seminal research articles on tendering by Friedman (1956), Gates (1967), and Vickrey (1961). Papaioannou et al. (2009) encountered a similar problem in their social sciences research and refused to "settle" for the most integrative bibliometric database. Google Scholar indexed the seminal publications in this study, but its database is less rigorous concerning peer-reviewed sources and does not provide a bulk export facility for quantitative bibliometric mapping (Martínez et al. 2015; Silber-Varod et al. 2016). Therefore, the approach taken in our first research stage (science mapping) was to rely on Scopus with the imputation of these seminals.

Maintaining a focus on B2B and B2G tenders in the scholarly literature in the English language, our search was restricted to journal articles, conference papers, books, and chapters. The Scopus subject areas were restricted to *business, management, accounting, and engineering*. All other subject areas were explicitly excluded in our search to avoid false positives unrelated to our area of inquiry. In addition, the academic literature on pricing is skewed toward consumer-based research (Indounas 2009), which is why the word "consumer" was another exclusion criterion in the title, abstract, or keywords. The search produced 1,481 journal publications until the year 2022. The following search term was used (in Scopus syntax for replication by other researchers)[2]:

> (TITLE-ABS-KEY (("tender*" OR "request for proposal" OR "request for quot*" OR "request for inform*" OR "bid" OR "bidding" OR "major sale*" OR "solution sell*" OR "sales manage*") AND ("industr*" OR "business to business" OR "b2b" OR "business to government" OR "b2g" OR "project" OR "procure*" OR "auction*" OR "price" OR "pricing"))) AND (TITLE-ABS-KEY ("*model*")) AND NOT TITLE-ABS-KEY ("consumer*" OR "energy" OR "electricit*") AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRC-

[2] When this search term is rerun in the future, it will produce more publications as Scopus constantly increases its database.

TYPE, "p") OR LIMIT-TO (SRCTYPE, "b")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ch") OR LIMIT-TO (DOCTYPE, "bk")) AND (EXCLUDE (SUBJAREA, "COMP") OR EXCLUDE (SUBJAREA, "ENER") OR EXCLUDE (SUBJAREA, "ECON") OR EXCLUDE (SUBJAREA, "MATH") OR EXCLUDE (SUBJAREA, "DECI") OR EXCLUDE (SUBJAREA, "SOCI") OR EXCLUDE (SUBJAREA, "ENVI") OR EXCLUDE (SUBJAREA, "MEDI") OR EXCLUDE (SUBJAREA, "MATE") OR EXCLUDE (SUBJAREA, "EART") OR EXCLUDE (SUBJAREA, "AGRI") OR EXCLUDE (SUBJAREA, "PHYS") OR EXCLUDE (SUBJAREA, "ARTS") OR EXCLUDE (SUBJAREA, "CENG") OR EXCLUDE (SUBJAREA, "PSYC") OR EXCLUDE (SUBJAREA, "MULT") OR EXCLUDE (SUBJAREA, "BIOC") OR EXCLUDE (SUBJAREA, "CHEM") OR EXCLUDE (SUBJAREA, "PHAR") OR EXCLUDE (SUBJAREA, "NEUR") OR EXCLUDE (SUBJAREA, "HEAL") OR EXCLUDE (SUBJAREA, "NURS") OR EXCLUDE (SUBJAREA, "IMMU") OR EXCLUDE (SUBJAREA, "VETE") OR EXCLUDE (SUBJAREA, "DENT")) AND (LIMIT-TO (LANGUAGE, "English"))

Based on a manual inspection of the titles, abstracts, and keywords for the most-cited 100 publications, however, 35 keywords were identified to cause false positives. They were then added to the search term as exclusion criteria, culling the number of publications to 1039. The added exclusion criteria are as follows (again in Scopus syntax for replicability):

EXCLUDE (EXACTKEYWORD, "Model Buildings") OR EXCLUDE (EXACTKEYWORD, "Design") OR EXCLUDE (EXACTKEYWORD, "Electric Industry") OR EXCLUDE (EXACTKEYWORD, "Architectural Design") OR EXCLUDE (EXACTKEYWORD, "Power Markets") OR EXCLUDE (EXACTKEYWORD, "Budget Control") OR EXCLUDE (EXACTKEYWORD, "Electricity Market") OR EXCLUDE (EXACTKEYWORD, "Investments") OR EXCLUDE (EXACTKEYWORD, "Electric Utilities") OR EXCLUDE (EXACTKEYWORD, "Sustainable Development") OR EXCLUDE (EXACTKEYWORD, "Design Build") OR EXCLUDE (EXACTKEYWORD, "Resource Allocation") OR EXCLUDE (EXACTKEYWORD, "Design/methodology/approach") OR EXCLUDE (EXACTKEYWORD, "Electric Power Systems") OR EXCLUDE (EXACTKEYWORD, "Electric Power Generation") OR EXCLUDE (EXACTKEYWORD, "Building Information Model—BIM") OR EXCLUDE (EXACTKEYWORD, "Public Private Partnerships") OR EXCLUDE (EXACTKEYWORD, "Project Delivery") OR EXCLUDE (EXACTKEYWORD, "Quality Control") OR EXCLUDE (EXACTKEYWORD, "Design-build Projects") OR EXCLUDE (EXACTKEYWORD, "Societies And Institutions") OR EXCLUDE (EXACTKEYWORD, "Design-build") OR EXCLUDE (EXACTKEYWORD, "Laws And Legislation") OR EXCLUDE (EXACTKEYWORD, "Productivity") OR EXCLUDE (EXACTKEYWORD, "Deregulation") OR EXCLUDE (EXACTKEYWORD, "Design-bid Build") OR EXCLUDE (EXACTKEYWORD, "Economic And Social Effects") OR EXCLUDE (EXACTKEYWORD, "Project Delivery Method") OR EXCLUDE (EXACTKEYWORD, "Technology Transfer") OR EXCLUDE (EXACTKEYWORD, "BIM") OR EXCLUDE (EXACTKEYWORD, "Electric Generators") OR EXCLUDE (EXACTKEYWORD, "Electric Power Transmission") OR EXCLUDE (EXACTKEYWORD, "Project Delivery Systems") OR EXCLUDE (EXACTKEYWORD, "Electric Power Transmission Networks") OR EXCLUDE (EXACTKEYWORD, "Electricity Markets")

After the imputation of the seminal articles by Friedman (1956), Gates (1967), and Vickrey (1961), 1,042 publications were available for a science mapping analysis. The publications were then evenly distributed across four periods to mitigate the suppression of emerging themes in the science mapping procedure. This produced the following periods: 1956–2005, 2006–2011, 2012–2017, and 2018–2022. A surprising finding at the start of this science mapping stage was that the field of *engineering was still the dominating Scopus subject area with a publications share of* 59.8% *versus business, management, and accounting's share of* 40.2%. The latter share included the sales and marketing (S&M) literature, which has a deep grounding in pricing research (Kienzler and Kowalkowski 2017; Roll 2009). This grounding could have led to a naïve assumption that the pricing of tendered bids would be included adequately also in the S&M literature due to the size of the B2B/B2G deals involved (Rackham 2020; Toman et al. 2017; Dixon and Adamson 2013). However, this assumption will be debunked in Sect. 5 (RQ3: Meta-inference–a research agenda toward closing theory-to-practice gaps).

3.1 Quantitative parameters and thresholds

Systematic bibliometric reviews often confine themselves to listing Boolean searches in bibliometric databases and stepwise flow charts, such as PRISMA, as presented in this study so far (Papaioannou et al. 2009; Briner and Denyer 2012). For the replicability of this study, this section adds transparency by sharing the quantitative thresholds applied during the science mapping procedure. SciMAT Version 1.1.05 was chosen as the science mapping software due to its strong pre-processing and evolutionary mapping capabilities (Moral-Muñoz et al. 2020). We used *co-occurrences* of the publications' keywords (Chen et al. 2014) for mapping the evolution of tendered bidding in B2B and B2G. This approach has recently been used by other studies that combined systematic reviews and bibliometric methods (Vakkuri et al. 2019; Mas-Tur et al. 2019; Comerio and Strozzi 2019).

As a first filter to reduce publications only peripherally related to the search term as above under this heading, a minimum threshold of two simultaneous keyword co-occurrences was required for each publication across its title, abstract, and keywords, as shown in Table 1.

Following the recommendations of Cobo et al. (2011), the publications were then grouped into *thematic clusters* for each period according to their *equivalence index*. This index analyzes how often keywords appear together in publications to measure their equivalence. The equivalence index is 100% if keywords are always associated or zero when they are never co-listed by an author (Herrera-Viedma et al. 2016). For each of the thematic clusters, *minimum and maximum thresholds* of five and eleven keywords were applied for cluster compactness, respectively. The *network edge reduction* parameter required linked thematic clusters across consecutive periods to share at least two keywords. These parameter thresholds are listed in Table 1 and were geared toward breadth rather than depth in terms of the compactness of bibliographic charts produced by science mapping and in line with the recommendations by Fisch and Block (2018).

3.2 Dual-criteria optimization of results

It must be emphasized that articles outside the parameter thresholds of Table 1 were excluded from science mapping. It is, therefore, common in science and bibliographic mapping that not every publication will be mapped. With the thresholds applied, the sum of publications included across all clusters was 700. However, the same publication might be included in multiple thematic clusters (Chen et al. 2014; Cobo et al. 2012), making 700 the upper limit for the count of mapped publications. We introduce the *mapping factor, MAPF*, as a new metric for the ratio of this upper limit over the total number of the included publications. This leads to the following equation: $MAPF = \sum \frac{c_{\mathrm{nm}}}{p}$, where c_{nm} is the count of publications included in cluster n of period m, and p is the total number of publications meeting the inclusion criteria, net of false positives. *MAPF* has been included in Table 2 as $\frac{700}{1{,}042} = 67\%$.

MAPF is an essential measure of mapping completeness when bibliographic maps are produced because researchers often give the (false) impression that all of their publications meeting the inclusion criteria on PRISMA charts have been mapped. However, science and bibliographic mapping rely on parameter thresholds, reducing the number of mapped publications from those identified in the inclusion criteria. This study's *MAPF* value of 67% is a satisfactory result for 1042 identified publications compared to other studies. For example, two different studies produced *MAPF* values of 63% for 2489 publications (Herrmann 2023a) and 15% for 25,379

Table 1 Science mapping parameters [source: authors]

Parameter	Threshold
Keyword co-occurrence per publication	2
Minimum keywords per thematic cluster	5
Maximum keywords per thematic cluster	11
Network edge reduction across periods	2

Table 2 Optimization criteria for the selection of parameter thresholds [source: authors]

Optimization criterion	Result
Mapping factor, *MAPF*	67%
Average *h*-index across clusters	10

publications (Herrmann 2022), respectively. Another cross-disciplinary research produced *MAPF* values of 77% for 828 publications from the first field and 30% for 2489 publications from the second field (Herrmann 2023b).

The *h*-index (Hirsch, 2005) was considered an additional criterion to *MAPF* to enhance the robustness of this study's results. The *h*-index of a thematic cluster measures the *impact* of its included publications by combining quantitative factors (i.e., publication counts) and qualitative factors, i.e., citations (Mas-Tur et al. 2020; Santana and Cobo 2020). Hirsch (2005) states that an *h*-index of 20 over 20 years is a good result. Considering that 42% of the mapped publications were from the 11 years 2012–2022, an average *h*-index of 10 across all clusters indicates that, overall, the identified clusters reasonably impacted the literature of tendered bids in B2B and B2G (Cobo et al. 2011). However, not every cluster has contributed equally, and a substantial variation among clusters is discussed in the next section, 3.3.

Parameter thresholds were iteratively varied to maximize the *h*-index and *MAPF* in a dual-criteria optimization, as listed in Table 1. Unfortunately, the *h*-index, MAPF, and quantitative parameter thresholds are inconsistently (or rarely) reported in systematic bibliometric reviews of business fields (Herrmann 2023b). This poses a substantial problem for the replicability of research by others and the assessment of a study's robustness because results can vary significantly for different thresholds in Table 1 (Herrmann 2023a). We hope this research generates such awareness and leads to a more transparent publication of the *h*-index, *MAPF,* and parameter thresholds in bibliographic and science mapping.

3.3 Science mapping results

The evolutionary and overlapping maps in Figs. 2 and 3 have been visualized with the *inclusion index*. The index is relevant for the strength of links between thematic clusters across consecutive periods (Bianco et al. 2021). The index is also helpful for integrating diverse or multidisciplinary subjects (Sternitzke and Bergmann 2009), as was the case in this study, between the fields of engineering, business, management, and accounting.

3.3.1 Evolutionary map

Solid lines across periods in Fig. 2 show linked thematic clusters sharing at least two keywords. Dashed lines denote clusters sharing just one keyword. The thickness of solid or dashed lines is proportional to the strength of a relationship between concepts as per the inclusion index (Cobo et al. 2011). Tracing solid and dotted lines across the thematic clusters defines a *thematic area*, which depicts how concepts have developed into others and across sub-concepts (Herrmann 2022). A cluster's *h*-index (Hirsch 2005) is shown within its corresponding sphere to measure its impact on the scholarly literature.

Three thematic areas were identified for B2B and B2G tender modeling in Fig. 2 and ranked according to their average *h*-index as follows:

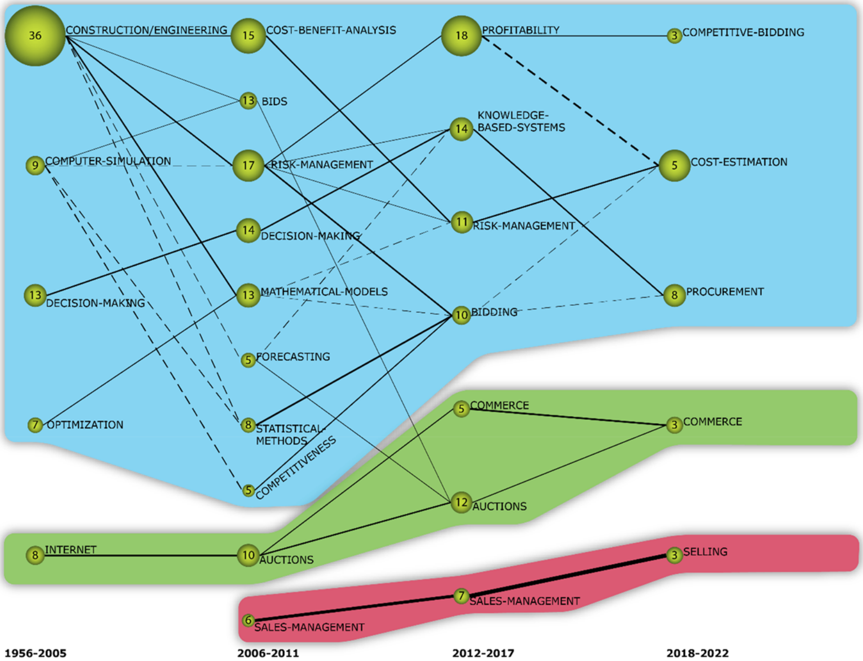

Fig. 2 Evolutionary map of competitive bidding with the sphere size proportional to the *h*-index (source: authors, based on SciMAT output)

1. Construction and engineering in blue color; average *h*-index of clusters = 12
2. Electronic commerce (or "e-commerce) in green color; average *h*-index of clusters = 8
3. B2B S&M management in red color; average *h*-index of clusters = 5

On visual inspection of the *h*-index, thematic clusters varied substantially in their impact on the research corpus. Grouping the clusters by their thematic area produced the above ranking according to the average *h*-index for cluster memberships. In the first period, 1956–2005, the construction/engineering cluster had the highest *h*-index at 36 across all clusters and periods. This dominance continued for that thematic area in the second period, 2006–2011, with *h*-indexes of 17 for risk management and 15 for cost–benefit analysis. Profitability dominated the third period, 2012–2017, with an *h*-index of 18. Despite the overall dominance of the thematic area for *construction and engineering*, not nearly as much impactful research has been published in the latest period, 2018–2022. This can be explained, of course, by a shorter period for gathering citations versus the previous periods' advantage of earning more citations over time. However, an important observation is that the selling perspective on tendering shifted toward procurement, taking a greater interest in tendered pricing models from a purchasing perspective with the highest h-index of 8.

E-commerce can be defined as e-commerce = organization + market mechanism + trust (Sierra 2004). As a thematic area, it had an average *h*-index of 8. Auctions had strong linkages with the construction/engineering themes of forecasting and bids. Among the most-cited publications with such linkages (sampled from the SciMAT results across periods and other than seminal articles) were those (1) with a focus on artificial intelligence (Chou et al. 2015; Korb and Sacks 2021; David et al. 2002); or (2) a focus on auction theory (Xu and Huang 2015; Jap and Naik 2008; Rothkopf 2001); or (3) journal articles that provided linkages with "auction" in the articles' keywords although the contents were more of a probabilistic than auction-theoretic focus (Ballesteros-Pérez et al. 2013, 2014; Skitmore 2004), or (4) dealt explicitly with applications of radio spectrum auctions (Xiang et al. 2012; Stanojev et al. 2009; Rajasekharan et al. 2011).

The thematic area of B2B S&M management did not emerge until the second period, 2006–2011, and spanned an *h*-index of just 3–7. In addition to its low impact on the academic tendering literature, Fig. 2 showed a disconnection from the other two thematic areas for tendering. This suggests a gap between the *scholarly* literature on B2B S&M management versus the modeling of tendered bidding in the fields of construction, engineering, and e-commerce. The most cited publications across periods, however, provide valuable insights into theory-to-practice gaps (Matthyssens and Johnston 2006; Piercy 2010; Schmitz and Ganesan 2014; Böhm et al. 2020), which will be discussed in Sect. 5. Other publications related to model conceptualizations that are not tender-pricing-related (Agnihotri et al. 2016; Guesalaga 2016; Itani et al. 2022).

3.3.2 Stability of the evolutionary map

Figure 3 provides insights into the longitudinal stability of the evolutionary map in Fig. 2. Each sphere denotes a period with its corresponding number of keywords at its center. The number of shared keywords between consecutive periods is shown on the horizontal connectors and their inclusion index in brackets. The angled connectors show the number of out- and inflowing keywords between periods.

The first period (1956–2005) covered fifty years, followed by two six-year periods and a 5 year time frame. The considerable variation between the first and subsequent periods must be considered when interpreting Fig. 3. A 70% carry-over of keywords from the first period (1956–2005) to the second period (2006–2011) is not

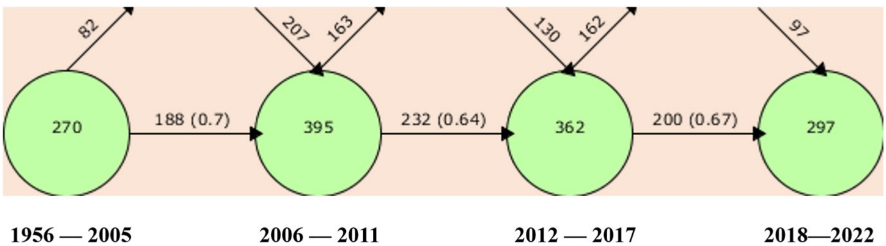

Fig. 3 Overlapping map (source: authors, based on SciMAT-produced visualization)

a surprise, given the second period was only 12% of the length compared to the first. The substantially large number of 207 keyword additions is also no surprise because the thematic area of B2B S&M management entered the evolutionary map in the second period of Fig. 2. The inflow of new keywords declined after that entrance over the remaining periods. However, a low 64% keyword "survival" rate into the third period of equal length (2012–2017) suggests a shift within the thematic areas emerged. This shift appears to carry on into the most recent period (2018–2022) with 67% of keywords transferred, but that period is one year shorter. Indeed, the number of keywords in the first period (270) is almost the same as in the most recent period (297) after a substantial rise in the intermediate periods (395 and 362). This suggests that the field is substantially in flux and not consolidating in the academic domain. The following section explains that this shift is mainly caused by advances in auction theory (Sect. 4.2) and artificial intelligence (Sect. 4.5).

4 RQ2: Narrative review of the academic and gray literature—revealing schools of thought and their theory-to-practice gaps

In stage two of this research, we conducted a narrative literature review from the scholarly as well as the gray literature to balance scholarly and practitioners' views. Journal articles, conference papers, books, chapters, dissertations, reports, and trade journals were considered in a snowball procedure (Wohlin 2014). The most-cited publications identified in the previous science mapping review provided the starting point. Their full texts were processed, and their references were traced. In a recursive procedure, the references in the references were then traced back to seminal tendering publications (Friedman 1956; Gates 1967; Vickrey 1961).

Consequently, this second research stage mitigated the coverage limitations of Scopus (Martín-Martín et al. 2018) and added depth to the relatively broad results shown in the evolutionary map in Fig. 2. A substantial number of 241 full texts were processed, but 78 were excluded, mainly from the gray literature. Other research by Mourão et al. (2020) also found the combination of Scopus with a snowball procedure from another database (in this study's case, Google Scholar and the gray literature) more effective in covering breadth and depth. This hybrid snowball procedure revealed seven schools of thought with substantial differences in their methodologies to develop models for tender pricing. We assess the causes of theory-to-practice gaps for each of the identified schools.

4.1 The probabilistic school—in search of a theory for tendering

This school of thought evolved in the thematic area of construction and engineering in Fig. 2. The seminal model by Friedman (1956) is generally credited with setting the cornerstone of interest in *probabilistically* modeling the lowest price of tendered bids (Ballesteros-Pérez et al. 2021; Ioannou 2019). The prevailing "cost-plus" or "bottom-up" pricing approach in tendering practice (at the time as well as today) is explicitly considered by multiplying a project's estimated cost with a mark-up for covering risk, profit, and overheads (Liu et al. 2018; Urquhart and Whyte 2018; Venkataraman and Petersen 2022; Zaqout et al. 2022). However, another model published by Gates (1967) gave rise to a controversy in the scholarly literature. Initially, this controversy centered on a disagreement between Friedman's and Gates' models (Carr 1982; Fuerst 1977, 1979; Gates 1976, 1979). Then, the focus switched to their assumptions that competitors do not discriminate among tender opportunities and do not react to each other's bidding behavior (King and Mercer 1988; Runeson and Skitmore 1999).

Such assumptions simplified statistics-based models for the probability of winning at an optimal mark-up and deciding whether to bid (Urquhart and Whyte 2018). But these simplifications are unrealistic in practice (Adnan et al. 2018; Ballesteros-Pérez et al. 2012; Oo et al. 2022; Shokri-Ghasabeh and Chileshe 2016; Urquhart et al. 2017) with too much at stake for practitioners to rely on them for "playing lottery" (APMP 2014; Skitmore 2002). Thus, several probabilistic model extensions have been proposed to include, among other considerations: (1) *unbalanced bidding*, in which a bidder varies the pricing of line items while keeping the total bid price constant (Nyström and Mandell 2019; Su et al. 2020); (2) *sales pipeline versus capacity to deliver* (Zahid et al. 2021; Zaqout et al. 2022); or most importantly, (3) the *accuracy of cost estimates* (Matel et al. 2019; Takano et al. 2018). On the latter point of cost estimation with its substantial weight as a mark-up multiplier, Morin and Clough (1969) stated quite early that the cost estimate is the principal predictor in bid pricing. Therefore, the accuracy of price predictions depends heavily on the accuracy of the cost estimate (Herrmann 2019; Skitmore and Runeson 2006; Runeson and Skitmore 1999). Various cost-estimation approaches have emerged, and there is much benefit in learning from past projects on both sides, bidders as well as buyers (Ballesteros-Pérez et al. 2021; Oo and Tang 2021; Xiong et al. 2019).

4.2 The auctioning school—in search of an economic theory

Another seminal article by Vickrey (1961) from the field of economics became a foundation for game-theoretic modeling of auctions for bidding and procurement. This has become known as "*auction theory*" (Skitmore 2014; Sierra 2004) and evolved to the most prolific area of publications in competitive bidding if we include B2C and C2C markets, such as (internet/online) auctions and the efficiency of alternative market mechanisms (Skitmore 2008; Whitford 2007). In B2B and B2G markets, auction theory also became a significant influence as game-theory-trained economists discovered tendering in the late 1970s and then incorporated competitive reaction into bid models for individual bids as well as on bids over time (Osborne 2009; Rothkopf 2001; Rothkopf and Harstad 1994). Figure 2 captures auction theory in the thematic area of e-commerce.

A significant contribution of auction theory relates to the *winner's curse* (Harstad and Pekeč 2008). This concept suggests that as an increasing number of bidders participate, the more likely the winning bidder will make a loss on the bid, even if that bidder's costs were not underestimated (Ahmed et al. 2016). Indeed, up to 15% of a tender's work hours are nowadays spent on avoiding the winner's curse, albeit not usually through formal models (Urquhart et al. 2017).

Models from auction theory have been too abstract for practitioners and modeled tendering processes through unrealistic simplifications similar to what was discussed earlier for the probabilistic school (Asgari 2020; Awwad et al. 2015; Skitmore 2008). A new research boom emerged in the 2010–2020 decade to bring these simplified models in line with the reality of price discovery by procurement departments (Haruvy and Jap 2012). Much research attention has been on mechanism design and format by incorporating differentiated bidders, tender evaluation scoring, negotiations, transparency (or manipulation) of information provided by buyers, and reputation (Haruvy and Jap 2022). This finding explains part of the earlier identified shift in Sect. 3.3 within the thematic areas of the evolutionary map (Fig. 2) and its overlapping map (Fig. 3).

Electronic marketplaces ("B2B hubs" or "B2B exchanges") often offer pricing mechanisms through auctions and have been a keen interest in industry practice and academia since the turn of the last century (Kaplan and Sawhney 2000). During the dot-com boom between 1995 and its crash in 2000, numerous electronic marketplaces were launched commercially, but most were wiped out in the crash (Schmitt 2019). Only a few B2B exchanges exist today with challenges in a commercially sustainable business model for them, substantial organizational and technological change management requirements on the bidder and buyer sides, security and neutrality concerns, and requirements of the regulatory environment in which they operate (Rashidi et al. 2023; Shankar 2022; Shree et al. 2021).

Exchanges differ from *electronic tendering* ("e-tendering") as the latter is not an open concept to facilitate transactions between bidders and procurement. Electronic tendering follows procurement-specific processes that are (partially) automated (Qusef et al. 2019). Its uptake has been recommended to address the United Nation's Sustainable Development Goal 12.7 for B2G tendering (Raiden and King 2021) but has been slow mainly due to concerns about security and confidentiality (Al Yahya et al. 2018; Aibinu and Al-Lawati 2010).

4.3 The top–down school—a practice-oriented search for an optimal price without theory

With a focus on regression methods, the "top–down school" emerged from operations research parallel to probabilistic models and auction theory. It is not covered well by Scopus and is therefore not included in any of the thematic areas of Fig. 2. Here, it is assumed from *competitive intelligence* that an individual bidder makes systematic price variations against an aggregate of competitors or identified "key competitors" based on specific market conditions, such as the type and size of the project, degree of corruption, project location, number of competitors, risk, or other variables, but typically not in competitive reaction to other bidders (Ballesteros-Pérez et al. 2021; Shokri-Ghasabeh and Chileshe 2016; Zhang et al. 2017). In this approach, bid pricing is modeled in a data-driven way from historical data, and alternative strategies are then simulated to inform practitioners about probable future outcomes (Herrmann 2019). Such simulations are also helpful for the decision to bid (Oo et al. 2022; Zaqout et al. 2022). As this approach requires decisions about which market conditions to include, model re-estimates may be necessary to improve bidding performance and ensure the competition has not changed its bidding strategy (Osborne 2009; Herrmann 2000).

This approach is paradigmatically different from probabilistic and auction-theoretic models as historical bidding data inductively drive it without deduction from theory, akin to what is known as "business intelligence" today (Herrmann 2022). Its models are often also agnostic to the practice of mark-ups due to their focus on market factors (Herrmann 2019; Kingsman and Mercer 1997). However, statistical overfitting becomes a problem with data-driven models if less than five historical contracts are available for every market factor included in a model (Hair et al. 2019). Such a minimum number of competitors' bid prices is often difficult to obtain unless they are published and publicly available (Ballesteros-Pérez et al. 2021, 2013; Skitmore 2002). Querying (typically risk-averse) salesforces for competitors' pricing data leads to unreliable information (Venkataraman and Petersen 2022).

Modeling techniques used in this school often maximize the likelihood of weighted regression models, which require the skills of a data scientist or statistician (Herrmann 2022). However, once developed, practitioners can quickly deploy these models with only incremental change management requirements in the bid process (Herrmann 2000). For example, when a request for tender is received, the bid team would meet with the data scientist to provide historical data on bidding results, including the market conditions for each bid. The bid team would then customarily prepare their bid. Simultaneously and independently, the data scientist would fit a top–down model to the data and simulate alternative bidding strategies. The simulation results would be used by the bid team as an additional piece of information for the pricing decision as well as the bid/no-bid decision.

It would be fair to credit Mercer and Russell (1969) for their seminal work in the top–down school in the oil industry. Other practical applications have been found in manufacturing (Kingsman and Mercer 1997), transport (Mercer and Tielin 1996), construction (King and Mercer 1991, 1985, 1987), and telecommunications (Herrmann 2019). But why have we found only one publication from this century? There are several conceivable reasons. One of them is that Professor Alan Mercer, arguably the galvanizing force of this school, retired in 1998 and passed on in 2014 (Elsevier Obituary 2015). Another reason might be that holdout samples (Xiong et al. 2019) were not consistently applied, given the limitations of access to a sufficiently large data sample of tenders and therefore affecting generalizability (Herrmann 2000). Alternatively, successful practical applications may exist but have not been published in the public domain for reasons of competitive advantage. Or is it that business people "do not like to reveal their costs" to consultants for modeling (Rothkopf 2007) unless firm legal deeds that exceed non-disclosure agreements are implemented? The professional experience of the authors of this study could confirm this. To avoid any speculation on the recent publication hiatus of the top–down school, it shaped the next school, "price-to-win", with major practical applications today, as discussed next.

4.4 Price-to-win—in search of a "should cost" target for large bids

Price-to-win is also not covered sufficiently by Scopus and is therefore not included in Fig. 2. It is predominantly covered in the gray literature for practitioners. Price-to-win is based on customer profiling, customer relationships, competitive intelligence, and differentiated value, with a "design-to-cost" approach for designing a solution to the buyer's problem (Dax et al. 2019; Oo and Tang 2021; Pickar and Feely 2017; Retolaza et al. 2021). Price-to-win uses the above top–down approach to predict the market-clearing price (= winning bid price) and then works toward a bidder's cost target from competitive intelligence as follows (Newnes et al. 2014b; O'Guin 2017):

Bidder's cost target = predicted market-clearing price MINUS bidder's target margin MINUS bidder's risk allowance.

Thus, the bidder's cost target is viewed through competitive intelligence on the buyer's market-clearing-price decisions, considering the solutions competitors are likely to offer (Lorentz et al. 2020; Mandolini et al. 2018). From the competitive intelligence on historical data and current market conditions, the bidder optimizes its solution (and thus, its own cost) with its allowances for a target margin and risk toward the predicted market-clearing price (APMP 2014). When price-to-win is employed early in the bidding process, it can also solve the winner's curse through a "no-bid" decision (Brindley et al. 2017). However, it is self-evident that such an approach requires much competitive intelligence and effort. It is, therefore, more suitable to a bidder's most desirable sales opportunities and strategic pursuits when the cost of bidding is considered (Dalrymple et al. 2006; Hoeft et al. 2021). Evidence of price-to-win applications in practice is in computer software and services (Chirra and Reza 2019; Herglotz 2015; Mansor et al. 2011; Molokken and Jorgensen 2003), defense contracts (Brindley et al. 2017; O'Guin 2017; Pickar and Feely 2017), and high-value manufacturing (Bevilaqua 2021; Newnes et al. 2014a, 2014b; Visseren 2017).

4.5 Artificial intelligence—a trend toward the "what" at the expense of the "why" and "how"

Artificial intelligence (AI) is a broad field with a long history of academic research in the thematic areas of construction, engineering, and e-commerce, as shown in Fig. 2. Advances in AI significantly contributed to the earlier identified shift of keywords in Sect. 3.3.2, which discussed the overlapping map in Fig. 3.

The origin of AI is based on knowledge-based systems, which have evolved from bidding applications to become relevant to the procurement function, as seen in the latest period, 2018–2022, in Fig. 2. Figure 4 shows the relationship between such

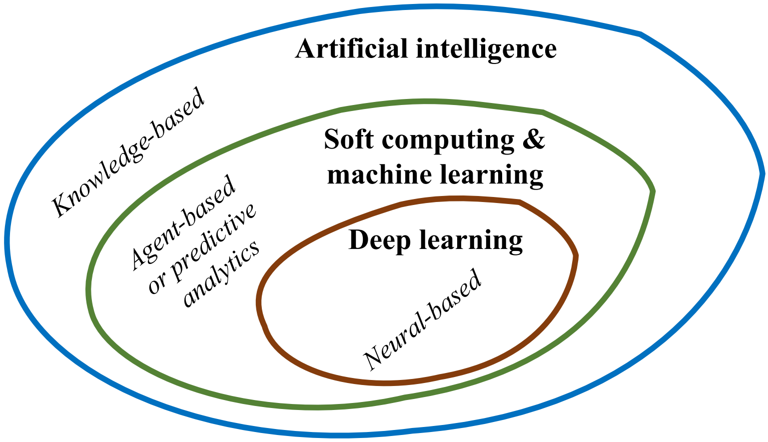

Fig. 4 Interrelationships between artificial intelligence frameworks in tendering (adapted from Ashta and Herrmann 2021 with permission)

"good old fashioned AI" (Herrmann 2022) and its more recent developments in soft computing, machine learning, and deep learning, specifically in a tendering context.

Knowledge-based systems involve various technologies to acquire explicit and tacit knowledge and then reuse it, such as in wikis (Grudin 2006). AI-oriented approaches mimic the problem-solving capabilities of human experts through a structured representation of knowledge (Garnelo and Shanahan 2019). So-called "knowledge engineers" create "if–then" rules by interviewing experts on their experience (Dick 2019). Knowledge-based systems have been deployed across all periods of Fig. 2 on both sides of bidding and procurement (Akcay and Manisali 2018; Chua et al. 2001; Nieto-Morote and Ruz-Vila 2012; Plebankiewicz 2009). However, research by Hu et al. (2016) argues that tender pricing decisions are "too complicated and un-structured to model by a rigid rule-based process" and that knowledge-based systems are used to assist in tender pricing indirectly, for example, through identifying competition, risk and opportunity.

Soft computing and machine learning are separate branches of AI, but they both use deep learning technologies (Kelleher et al. 2020), which is why they were combined in Fig. 4. Both AI technologies have been deployed extensively in our Scopus extract. The difference is that soft computing deals with optimization, including uncertainty and approximation, whereas machine learning generates models that identify patterns to make predictions (Herrmann 2022).

In *soft computing*, the terms "multi-agent systems" and "agent-based models" are often conflated (Niazi and Hussain 2011). The first term was more dominant in our Scopus extract, but we have treated the terms synonymously. As such, agent-based models in computer software have been used extensively from the first period, 1956–2005 (David et al. 2002; Ito et al. 2000) and carrying through other periods (Koppensteiner et al. 2009; Asgari et al. 2016) to the most recent period, 2018–2022 (May et al. 2021; Asgari 2020). In the thematic area of e-commerce in Fig. 2, applications were in agent-mediated commerce (Renna and Argoneto 2013; Sierra 2004). In construction and engineering, the focus was more on simulation as an alternative to the deductive and inductive approaches from the probabilistic and top–down schools (Awwad et al. 2015).

Learning algorithms, such as supervised, unsupervised, and reinforcement learning, are employed in *machine and deep learning* (Schlenker and Minhaj 2020). These algorithms create a statistical "conversation" between input and output data until the input data predicts the output data well (Benaich and Hogarth 2020). This learning process is time-consuming and computationally intense. Once completed, however, the software code generated by the learning algorithm runs fast and efficiently (Herrmann and Masawi 2022). Machine and deep learning have been deployed extensively in our Scopus extract across all periods (Wanous et al. 2003; Wilmot and Mei 2005; Cheung et al. 2006; Moon et al. 2021).

The problem with learning algorithms is statistical overfitting (He et al. 2021), and there is often little interpretability of how these entirely data/statistically driven models work. Such models tend to prioritize predictions (i.e., the "what) over the explanatory power of "why" and "how", which often leaves practitioners (as well as researchers) with an opaque "black box" (Herrmann 2023b). These problems are compounded in deep learning, which employs neural networks with multiple internal layers (Borges et al. 2021). Therefore, decision-making with deep learning is not based on theory or practitioner experience (Serrao 2021).

Algorithmic game theory has emerged to address theory by fusing the fields of artificial intelligence and game theory. However, this fusion is part of the field of microeconomics (with a focus on market mechanisms) and does not bridge theory-to-practice gaps for tender practitioners (Elkind and Leyton-Brown 2010; Roughgarden 2008).

Industry practice does have major use cases for *S&M automation with AI support*, although commercial software platforms are mainly consumer oriented (Haleem et al. 2022). Commercial products for B2B/B2G practice do not directly address tender pricing and are geared toward the front-end of S&M processes, such as lead generation, qualification, multichannel customer engagement for progressing leads, and using analytics for measuring performance (Romero 2019; Sherer and Cleghorn 2018). Gartner, a global research and consultancy company, regularly publishes a "hype cycle" on various information technologies (Perez and Kreinovich 2018). They placed AI-supported S&M automation into a "trough of disillusionment," describing the technology as immature (McGuire and Leachman 2021) and providing a listing of commercially available B2B platforms (Gartner 2023). There is substantial interest from industry practitioners in AI-enabled S&M automation. Still, little scholarly research is available today (Voss et al. 2023), so most of the literature is gray (Tobon 2017).

4.6 The Skitmore school—fundamental research to address theory-to-practice gaps

In response to the problems discussed for the previous schools, some efforts are being made to integrate the bidding and procurement sides. Fundamental tendering research

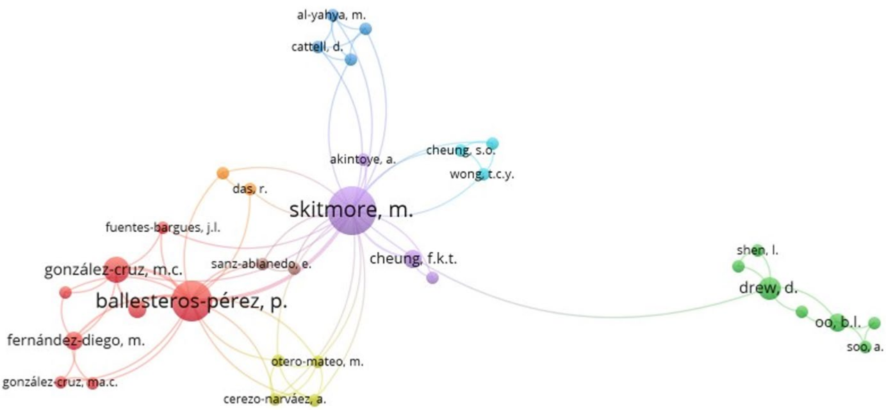

Fig. 5 Co-authorship network for the extended Skitmore cluster (Source: authors, based on VOSviewer visualization of extracted Scopus data)

is being conducted to understand better the principal bidding and procurement influences and their interrelationships, culminating in bidding or procurement strategy implications (Ballesteros-Pérez et al. 2021; Liu et al. 2018; Xiong et al. 2019; Zhang et al. 2017). However, this is research in progress, led by the thematic area of construction and engineering in Fig. 2, and with only incremental guidance to practitioners until the underlying tendering mechanisms are more generalizably understood from empirical evidence.

The associated literature with such research might be termed the "*Skitmore*" cluster of researchers, considering the influence of Martin Skitmore and his substantial contributions, with an *h*-index of 89 overall and 63 since 2019 (Google Scholar 2024). Skitmore's overall h-index goes back to the inception of a scientific approach to tendering. Figure 5 depicts a Scopus extract of Skitmore's (Scopus ID: 7003387239) extended co-authorships.

We included the networks for Skitmore's co-authors if they had at least six relevant publications, such as Pablo Ballesteros-Pérez (Scopus ID: 54782096900), Derek S. Drew (Scopus ID: 7102081577), Bee Lan Oo (Scopus ID: 16307956100), M. Carmen González-Cruz (Scopus ID's: 35221451300 and 57955540200), and Hinpro Lo (Scopus ID: 56047521000). The latter author is the unlabeled sphere in the green cluster between Drew and Oo in Fig. 5, which VOSviewer did not explicitly label without zooming into the spheres. It should be noted that Fig. 5 does not include publications outside of Scopus and full author counting was used versus fractional counting (Perianes-Rodriguez et al. 2016). Despite these restrictions, we still hope to give appropriate credit to authors involved in researching to understand the "what", as well as the "why" and "how", to bring together the bidder's and the procurement side's vantage points from practical as well as theoretical perspectives.

5 RQ3: Meta-inference—a research agenda toward closing theory-to-practice gaps

In this section, we provide a *holistic triangulation* (Bazeley 2020, 2019) of the quantitative (Sect. 3) and qualitative (Sect. 4) results, which contribute different elements to provide a deeper understanding. In other words, the different results are seen as complementary. The integrated results are tabulated in Table 3 and then discussed to develop a future research agenda for three specific roles in tender pricing.

5.1 A seventh school emerges—key account management and solution selling

A central observation from Table 3 is that our meta-inference adds a seventh school to the qualitative results of Sect. 4, "key account management and solution selling." This school was not revealed by the snowball procedure for the qualitative results, although it was included in the thematic area of B2B S&M management from the quantitative results of Sect. 3 (Davies and Ryals 2009; Böhm et al. 2020; Tienken et al. 2022). In other words, the qualitative results suggest that only scant linkages exist between tender pricing models and B2B S&M. The science mapping results in Fig. 2 show a complete disconnect of B2B S&M from the other two thematic areas that explicitly deal with tender price modeling in construction, engineering, and e-commerce. Some previous studies have also argued that B2B S&M has not yet been sufficiently integrated with the scholarly literature on tender pricing models (Skitmore and Smyth 2007; Skitmore 2008).

We now explore these scant linkages between tendering and the school of key account management and solution selling. Tendering is a highly interdisciplinary effort, which involves the substantial literature of *key account management* to pursue non-transactional, long-term relationships and exert influence over the customer's tendering process (Bornemann and Hettich 2022; Toman et al. 2017; Zahid et al. 2021). Sometimes, key account management is referred to as "strategic account management" (Storbacka et al. 2009). Research by Dax et al. (2019) from 428 tenders across different buying organizations shows that the quality of the salesperson's relationship with the buyer influences the buyer's evaluation of the tender. In the interest of longitudinal relationships, bidders often make pricing concessions on their bids (Hoque and Rana 2019).

In addition, tendering often involves the delivery of project-based solutions, which is why the literature on *solution selling* is highly relevant (Böhm et al. 2020; Peppers and Rogers 2016; Crespin-Mazet et al. 2019; Venkataraman and Petersen 2022). For that reason, solution selling has been explicitly included in the Boolean search term from Sect. 3. According to Storbacka et al. (2011), solution selling involves "longitudinal relational processes, during which a solution provider integrates goods, service, and knowledge components into unique combinations that solve strategically important customer-specific problems, and compensated based on the customer's value-in-use." Such deeper relationships sometimes result in "partnering", whereby both parties contribute toward a solution (Brook 2016). Therefore,

Table 3 Integration of qualitative and quantitative results

School	Focus and perspectives	Qualitative results for methodological approaches and research-to-practice gaps	Quantitative results for thematic areas
Probabilistic bid models	A theory for tendering; bidding and procurement perspectives	Univariate and multivariate statistics; pricing distributions from historical data or theory; deductive approach with simplifications unsuitable for bidding practitioners	Construction and engineering
Auctioning models	Economics (econometric modeling and pricing with JEL classifications C57 and D44, respectively); bidding and procurement perspectives	Originally, simplifications based on rational (often profit-maximizing) bidders with fixed pricing distributions and abstract models that are difficult to understand by bidding practitioners; much theoretical progress was made in the 2010–2020 decade through integrating auctions and negotiations more realistically	E-commerce
Top–down models	Optimal price without theory; bidding perspective	Often uses regression models that consider multiple market conditions; requires data from at least five contracts for each variable (= market condition); the data are gathered from public sources and competitive intelligence; models are complex to develop but easy to apply by practitioners with incremental change management requirements for bidding procedures; only six publications were found	Outside Scopus and thus not captured in the quantitative results of Fig. 2
Price-to-win models	Optimal price of a major bid; bidding perspective	Combines top–down models for market pricing with a design-to-cost approach; practical applications in strategic pursuits from various sectors; transformational change management requirements for the bidding process (often facilitated by external/consultancy advice)	Mainly in the gray literature and thus not captured in the quantitative results of Fig. 2

Table 3 (continued)

School	Focus and perspectives	Qualitative results for methodological approaches and research-to-practice gaps	Quantitative results for thematic areas
Artificial intelligence	Data-driven predictive analytics; bidding and procurement perspectives	Traditionally, knowledge- or soft-computing-based approaches; increasingly based on machine learning with emerging software products for automation in S&M, but without tender pricing support	Construction and engineering; e-commerce; AI in S&M is mainly in the gray literature and has not been captured in Fig. 2
Skitmore school	Fundamental research that seeks to integrate bidding and procurement perspectives	Originated from the probabilistic school; provides incremental guidance to practitioners on bidding influences and their interrelationships; no generalizable, prescriptive pricing models for practitioners to date	Construction and engineering
Key account management and solution selling	In pursuit of non-transactional, long-term relationships and exerting influence over the customer's tendering process; bidding perspective	Substantial peer-reviewed research emerged in this century beyond prescriptive and commercially touted methods, but tender pricing models are generally not included in the S&M corpus	B2B S&M management; this corpus is disconnected from the thematic areas of construction, engineering, and e-commerce in Fig. 2

much commercially available training on solution-selling opportunities and ensuing industry practice pivots on the value capture to refocus salespeople away from pricing toward dimensions of longitudinal relationship objectives and relationship qualifiers (Herrmann and Rana 2020).

5.2 The need for role-relevant research

Empirical studies in B2B S&M suggest that integrating theory with practice is challenging (Hinterhuber 2004; Ingenbleek 2007). Worse, this integration gap has been increasing for S&M decision models (Lilien 2011). Jaworski (2011) argues that *role-relevant research* is a requirement for closing theory-to-practice gaps by thoroughly understanding "a particular role in the organization" and selecting "a specific route to impact". However, the extant literature on tender pricing is immature in addressing role-relevant research. We propose how to address this next.

5.2.1 Three roles to focus on—sales directors, bid managers, and consultants

In search of crucial roles for the adoption of tender pricing models, we draw on the conclusions of a primary study of 337 questionnaire respondents from European business units in seven industries by Homburg et al. (2008), which revealed that the sales department has a more significant influence on pricing than the marketing function. These results lead us to suggest that the "*sales director*"—who is often also referred to as the "vice president of sales," "chief sales officer," "divisional sales manager," "regional sales manager," "sales leader," "branch manager," "area director," and "field sales manager" (Ingram et al. 2015)—is an appropriate role for future research.

Another key role in tendering is the *bid manager*, who often reports to the sales department and sometimes the commercial or legal functions (Nickson 2017). A bid has many characteristics of a project, in which a bid manager leads and coordinates the activities across a cross-functional bid team to develop a tender response within gated governance procedures of the bidder's organization (Laryea 2013; Smith 2017; Urquhart et al. 2017; Towner and Baccarini 2007). These integrating procedures increasingly reflect that selling and bidding are "increasingly about [a cross-functional] process, rather than a series of separate transactions carried out by a specific function" (Storbacka et al. 2009; Holma et al. 2020).

Practitioners are risk-averse and thus reluctant to adopt unproven models (Desai et al. 2012). The diffusion of innovation for knowledge management systems might help understand the factors impacting the adoption of mathematical models in practice (Okour et al. 2021): potential benefit, ease of use, and change management requirements. Hampton (2004, in Lilien 2011) argues that *commercial market research firms and consultancies* have traditionally been addressing these factors as "transfer agents" from theory to recognition of business benefits by industry and then toward early adopter pilots. It is, therefore, no surprise that outsourcing the decision support for tendering to external consultancies has become a regular practice, at least for major bids, which includes price-to-win approaches (Gartner Group

2022; Rashidi et al. 2023; Shipley 2022; O'Guin 2017). Therefore, consultants also play an essential role as intermediaries in closing gaps between theory and practice.

5.2.2 Three areas to focus on for each of these roles—timing and impact, knowledge needs for use cases, and relevance to practitioner tasks

Specifically for role-relevant recommendations in the solution-selling school, Salminen et al. (2013) propose to focus a research agenda on (1) timing of managerial implications (i.e., immediate versus future) and impact (i.e., trigger thought versus action); (2) knowledge needs of practitioners for use cases; and (3) relevance to a typology of managerial tasks, such as strategizing, coordinating, controlling, or transforming. Any research agenda must be specific to the roles of sales directors, bid managers, and consultants.

Concerning the *timing and impact* of the outcome of managerial relevance, the timing can occur in the *present* versus the *future*, and the nature of impact might be *thought* versus *action* (Jaworski 2011). It should be recognized that sales and bid managers have built mental models for tendering through many years of professional experience in their industry and prefer to rely on their business-savvy intuition over mathematical models (Lilien 2011). This may be a case of confirmation bias (Baker 2022), in which mathematical tendering models are interpreted by practitioners to confirm their prior beliefs and then rejected, although such models could help them understand how they can be applied in industries such as construction, engineering, and e-commerce. A future research agenda with an *immediate-thinking implication* could envisage breaking mental models and position mathematical tendering models as a tool for triggering a process of reflection. This would lead practitioners to codify their assumptions about tendering ("know-what") rather than purely relying on "know-how" from their skills and competencies (Johnson et al. 2002). A European primary study by Roll (2009) from interviewing 81 pricing practitioners supports the benefit of reflection. It suggests that academic and practitioners' views "should not be mutually exclusive, but can enrich the other's perspective".

Conversely, an agenda on *future-thinking implications* could envisage a scenario whereby most bidders could employ best practices for tender modeling. More practical models from the e-commerce school would then need to be developed to capture competitive reactions across bidders (Durugbo and Al-Balushi 2022; Venkataraman and Petersen 2022). Substantial work is in progress to help practitioners understand that best practice is sustainable under competitive reaction (Haruvy and Jap 2022, 2012). Still, it needs to be made more accessible to practitioners to give them confidence in adopting best practices.

For an example of *immediate action*, O'Guin (2017) provides a prescriptive step-by-step approach for the price-to-win school. A research agenda for *future action* could encourage sales and bid managers to identify consultancies with price modeling experience to engage one in a strategic tender in the future.

When *knowledge needs for use cases* are considered for solution selling in B2B S&M, the literature is dominated by empirical findings and lacks mathematical models (Salminen et al. 2013). However, the reverse is the case for the tendering literature, as discussed in the narrative review of Sect. 4. There are too many models and insufficient case studies or empirical evidence for their application. Hence, the Skitmore school focuses on empirical evidence. Price-to-win is the only school with empirical cases of applied tender pricing models, as shown in Table 3 and discussed in Sect. 4.4. However, the main contributions to that school are from the gray literature, which needs to go on the agenda for future academic research. Given the complexities of price-to-win procedures, the top–down school is an alternative candidate for future research because it requires only incremental change management and has practical use cases (refer to Sect. 4.3). Including this school in a future research agenda would revive it from its publication hiatus this century and address the knowledge needs of practitioners.

When viewed from a *typology of managerial tasks*, theory-to-practice gaps in tender models could be framed in terms of some of the sales directors' tasks in strategizing, transforming, and controlling (Storbacka et al. 2011). These tasks are increasingly shaped toward efficiency gains from automation through digital transformation in S&M industry practice (Guenzi and Habel 2020; Romero 2019; Sherer and Cleghorn 2018; Voss et al. 2023).[3] A limit to efficiency gains exists, as sales processes must comply with buyers' procurement processes, which bidders can rarely change unless they can reposition themselves as procurement advisors (Toman et al. 2017). Moreover, solution sales processes involve longitudinal relationships during the sales cycle, taking up to two years (Tuli et al. 2007).

With tendering typically occurring at the end of that cycle, a substantial cost of sales pursuit is incurred even before the cost of tendered bidding is assessed (Holma et al. 2020; Dax et al. 2019). The combined cost is substantial and can be expressed as a percentage of the total contract value (Hoeft et al. 2021). However, no rules of thumb were found in the literature as this percentage ratio varies across industries and market segments, and whether pre-tender costs were included in estimates (Dalrymple et al. 2006; Laryea 2013). Nevertheless, it is understandable that reducing the cost of selling through efficiencies in the bidding process is a topical issue in B2B S&M. Sales directors generally understand how to embed new decision-support tools (Jaworski 2011). Still, today, the focus is more on building a well-oiled sales machine (Voss et al. 2023) than on tender pricing models.

Due to the coordination task focus of most bid managers, they also appear to be more interested in improving the efficiencies of their bid production processes and procedures than in the effectiveness of bidding through models (Urquhart et al. 2017; Urquhart and Whyte 2018; Manchanda 2021). Therefore, a future research agenda should investigate how tender modeling could be injected into the current efficiency mindset. Table 4 summarizes the findings from our meta-inference and outlines a role-specific agenda for future research.

[3] See also the discussion in Sect. 4.5 on AI-supported S&M automation.

Table 4 A role-specific agenda for future research toward closing theory-to-practice gaps in tender price models

Targeted practitioner roles	Theory-to-practice gaps		
	Timing of impact (present vs. future) and nature of impact (thought vs. action)	Knowledge needs for use cases	Relevance to a typology of practitioner tasks
• Sales director • Bid manager • Consultant	• Immediate thinking: break practitioners' mental models • Immediate action: prescriptive and accessible step-by-step procedures for building and using price models • Future action: engage a consultancy on a future strategic tender • Future thinking: provide evidence for the sustainability of best practices under competitive reaction	Provide empirical cases for: • price-to-win • top–down school	Shift the current practitioner mindset from efficiency toward the effectiveness of tender pricing models for the following tasks: • Sales director: sales strategy, transformation, and control • Bid manager: bid strategy, coordination, and bid production Consultants need to recognize the value of pricing models in their tendering advice; a research agenda could frame this as a marketing opportunity for consultants

6 Conclusions

This study makes three contributions. First, applications of tender price models are scarce despite a substantial corpus in the scholarly and gray literature. Our research identified the causes of theory-to-practice gaps. We developed a research agenda with specific routes to advance the adoption of pricing models for three practitioner roles in tenders: sales directors, bid managers, and consultants. The agenda considers the timing and impact of implications, practitioners' knowledge needs, and tasks tied to these roles.

Second, this research addresses the need for more methodology-oriented literature reviews in business and management. SSM was introduced as a novel methodology for literature reviews by combining a systematic review and science mapping in a mixed-methods research design. The science mapping review charted the evolution of 1042 scholarly publications and aggregated them into three thematic areas from the period 1956–2022. A narrative review of 163 publications from the gray literature revealed seven schools of thought with substantial methodological differences for tender price modeling. Each of these schools has specific causes for their lack of adoption in practice. A meta-inference holistically integrated the qualitative and quantitative findings to develop a future research agenda, focusing on implications for closing theory-to-practice gaps. The interwoven, mixed-methods research design of this research and its large scale of publications contribute knowledge about methodologies for literature reviews.

In the third contribution of this study, we challenged knowledge about quantitative literature reviews in general. We exposed that the results of systematic reviews depend heavily on the parameter settings for their quantitative clustering techniques. It is less well known that these settings also determine which subset of the publications meeting the inclusion criteria is mapped. A smaller subset reduces the robustness of the results in systematic literature reviews. Therefore, we introduced a new metric, the mapping factor *MAPF*, to measure mapping completeness. If *MAPF* equals 1 (or 100%), all publication numbers typically shown on PRISMA charts are mapped. *MAPF* is proportional to a smaller subset and was 67% in this study, corroborating the robustness of our results compared to other studies for which we had access to data sets. We encourage researchers to publish *MAPF* values in their systematic reviews to indicate the robustness of their results. In addition, we remind researchers to report their parameter settings more consistently for transparency and replicability. Finally, we recommend publishing the *h*-index for literature clusters to measure impact.

7 Limitations

We want to acknowledge that a limitation of this research is a result of scholarly database limitations. None of the available databases sufficiently indexed publications from the last century. In other words, the field of tendering is fragmented across various indexing databases. Moreover, not much seminal research was found even when Scopus, Web of Science, EBSCO, Emerald, and ProQuest databases were combined. We encourage the database indexers to address this gap to enable learning from seminal research in tendering. However, this gap may not be easy to close, considering the commercial interests of the database providers. The best alternative database to Scopus in this research was Google Scholar, which was used in the qualitative stage of this study to mitigate the reliance on Scopus for the quantitative results. Due to its lack of a bulk export facility, however, Google Scholar was not a feasible database for the science mapping stage of our study.

Some readers might find the novelty of SSM challenging. This study calls for an open-minded approach that integrates the quantitative lens of scientometric research with the qualitative lens employed in narrative literature reviews. This fusion of quantitative and qualitative research methodologies, known as mixed-methods research, is often called the "third methodological movement". It has seen substantial growth since the turn of the century. While it continues to gain acceptance, we acknowledge that not all readers may be amenable to our research design. The strength of SSM lies in its ability to provide "thicker data" by integrating quantitative and qualitative inferences (Cameron and Herrmann 2023).

Integrating, mixing, and merging methodologies are a contemporary innovative trend in the mixed-methods scholarly community (Creamer and Schoonenboom 2018). In this sense, the mixed-methods design of SSM could be extended to reduce its reliance on reviewing the existing literature. We believe this limitation can be eliminated by incorporating primary research into the SSM framework. For instance, primary data collected through surveys, interviews, or observations could supplement the existing literature, providing a more comprehensive view of ways to close theory-to-practice gaps. This would reduce the reliance on the existing literature and allow for the inclusion of up-to-date and context-specific insights that may not be present in the extant literature.

Author contributions HH conceived the study, SSM, and MAPF. HH designed the research, collected and analyzed the data, and wrote the manuscript. MJCM contributed the evolutionary map, provided guidance on the SciMAT tool, validated the results, and proofread the manuscript. All authors have approved the submitted version and agree to be accountable for their contributions.

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Data availability The authors confirm that all data generated or analyzed are included in this published article. The data source for science mapping was Elsevier's Scopus database. The search term for extracting the publication data is presented in Sect. 3 in Scopus syntax for replicability by other researchers. The same section also shows the parameterization of the SciMAT tool for transparency.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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