Bus Inf Syst Eng
https://doi.org/10.1007/s12599-025-00930-w

RESEARCH PAPER

Conceptual Modeling Education

A Bibliometric Literature Review and Avenues for Future Research

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Received: 5 January 2024 / Accepted: 18 November 2024

Abstract Conceptual Modeling (CM) is a fundamental activity and discipline for many fields, including information systems, business engineering, and the natural sciences. Consequently, systematized and well-researched CM education is crucial for maintaining and developing CM as a research field and practice. Currently, CM as a discipline and, particularly, educational methods for teaching CM are fragmented. The present work presents a bibliometrical literature review filtering over 29,000 documents and obtaining 1064 publications associated with 24 (conceptual) modeling subtypes. Supplemented with applying semi-automatic content analysis, the study arrives at results providing a comprehensive overview of the field of CM education: prevalent CM subtypes, research methods and contexts, learning theories in CM education, as well as pertinent conceptual, intellectual, and social structures. The findings show conceptual, theoretical, and methodological research gaps, pointing to the potential for cross-CM subtype education. Existing intellectual and social structures focusing on a sole CM subtype neglect the potential benefits of considering education in tangential CM subtypes, as evident in the conceptual structure. Future research can draw upon the identified gaps, opening fruitful research directions for advancing the CM education field.

Keywords Conceptual modeling · Conceptual models · Conceptual modeling education · Bibliometric literature review · Semi-automatic content analysis

Accepted after two revisions by Hans-Georg Fill.

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1 Introduction

1.1 Conceptual Modeling (CM)

Conceptual Modeling (CM) is the process and discipline of describing aspects of the physical and social world through abstraction and conceptualization to understand, communicate, and manage complexity, primarily via describing the implicit mental models of the conceptual modelers into a typically visual format, such as diagrams (Mylopoulos 1992; Buchmann et al. 2019; Frank 1999). Focusing on articulating interconnected propositional knowledge units and concepts, conceptual models represent a fundamental part of the cognitive activities involved in understanding and learning about the world (Taber 2013). CM is associated with several purposes, the most important of which are to describe and to predict. Other objectives include training practitioners, educating the general public, discovering new questions, and promoting a scientific habit of mind (Epstein 2008).

Before 2005, CM was primarily focused on computer science modeling (e.g., data models). Between 2005 and 2020, there was a heightened emphasis on non-technical uses (e.g., business process modeling), the addition of an engineering perspective (e.g., software engineering), and a general interest in forming a generic theory of CM (Storey et al. 2023). Currently, CM is associated with and considered critical to knowledge-intensive and economically highly valuable areas (Storey et al. 2023). Examples include Databases and Software Engineering (SE), Artificial Intelligence (AI), Information Systems Engineering (ISE), Business Process Management (BPM; Guarino et al. 2020; Dumas et al. 2018), enterprise modeling (Vernadat 2002; Linden and Proper 2014), Model-Driven Architecture and Engineering (Verbruggen and Snoeck 2021), low-code programming (Bock and Frank 2021). CM is also used in conjunction with architecture and construction information modeling (Son et al. 2015), as well as in Scientific (Science) Modeling in general (Epstein 2008), and is critical for running simulations (Sokolowski and Banks 2010). The literature identifies multiple conceptual model types, including, but not limited to, value models (e.g., e-3), goal models (e.g., KAOS), process models (e.g., BPMN), information system models (e.g., UML), and multiple specific instances of languages, which are crucial to the many practical applications in business management, software engineering, and further areas (Guarino et al. 2020).

Recently, there has been an explicit call for collaboration and further interaction between CM research across different disciplines to build 'stronger cross-disciplinary ties' (Recker et al. 2021; Härer and Fill 2020; Lukyanenko et al. 2019). Research must deal with CM-related topics but can be primarily considered in other areas (Storey et al. 2023). As such, unifying CM theories and perspectives have begun to emerge (e.g., Buchmann et al. 2019; Härer and Fill 2020; Delcambre et al. 2021), as precisely the unifying theories are the most valuable (Taber 2013, p.238). While exploring topics beyond core CM is warranted, along with developing a set of commonly held assumptions across the CM subtypes, CM research does not focus enough on exploring the periphery of the diverse potential of subtopics (Storey et al. 2023).

In this research, we adopt a viewpoint that is centered on CM as a standalone discipline that is applied within the field of Information Systems (IS) engineering, encompassing specialized subfields like enterprise modeling, information systems engineering (e.g., UML and data models), as well as business, and (business) process modeling (Cabot and Vallecillo 2022; Ghiran et al. 2020). CM in these (sub)fields will henceforth be denoted as CM subtypes belonging to the 'core CM,' which aligns with our initial perspective.

Building high-quality conceptual models is critical for developing high-quality information systems since conceptual models are used to understand and elicit users' domain and system requirements. Furthermore, conceptual models provide a means for future system analysis – maintaining, modifying, extending, or repairing an information system – and are the critical component in model-driven engineering. Poor quality conceptual models may lead to misunderstandings and incorrectly designed systems and entail costly recovery and re-engineering efforts later in the information system life cycle (Nelson et al. 2012).

1.2 Conceptual Modeling Education

Learning and teaching CM has thus been an essential ingredient of IS, computer science, and business education for over fifty years, involving the necessity of teaching the complex cognitive activities of abstracting, conceptualizing, interpreting, and communicating (Rosenthal et al. 2023), which requires the understanding of syntactic, semantic and pragmatic aspects (Ulrich et al. 2023). However, CM's theoretical foundations and purposes, as well as its methods, artifacts, and assumptions, are often confined to the scope of a particular context, discipline, or expert domain. As a result, approaches to CM education tend to be restricted to specific CM subtypes and domains. Educators and students miss the opportunity to benefit from related pedagogical approaches in other CM subtypes, which hampers the potential cross-fertilization of ideas, theories, and approaches. This is particularly surprising as (re)engineering of modeling methods characterizes the field of CM, implying a specific cross-disciplinary knowledge of CM subtypes (Buchmann et al. 2019). Moreover, restricting research endeavors and exchange to teaching CM modeling subtypes and specific domains contradicts Recker et al.'s vision of citizen-oriented modeling (Recker et al. 2021) and Sandkuhl et al.'s idea of "enterprise modeling for the masses" (Sandkuhl et al. 2018).

Despite the relevance of CM education research, the research is still limited and fragmented (Rosenthal et al. 2019) and frequently focuses on a subset of issues. It is not understood broadly in the way that a broad understanding of CM was recently suggested (Cabot and Vallecillo 2022). Soyka et al. (2023) postulate that while there are many well-structured tasks in modeling education, there is a need for a broader and more comprehensive approach to cover all relevant competencies. Soyka et al. (2023) also emphasizes the importance of aligning educational tasks with the desired competences to prepare students effectively for professional challenges in modeling and related fields. Certain reviews focus on specific learning approaches, such as exploring the issue of automated (formative) assessment systems in CM education (Ulrich et al. 2023).

While previous reviews of CM research suggest that the importance of CM teaching should not be underestimated, a comprehensive overview which explicitly focuses on the field of CM education from a broader CM perspective is missing at present, which obstructs the educator's view of the state of the art and impedes cumulative research (cf. Section 3). Furthermore, we observe that teaching modeling is not systematized, with the curriculum often based on teachers' personal experience and understanding, leading to a wide diversity of didactical approaches. Learning outcomes of such pedagogical approaches are imbalanced, which leads to difficulties in both teaching and learning processes (Bogdanova and Snoeck 2017). There are cognitive differences between novice and expert modelers, the complexity of modeling languages and software tools, the absence of intensive trial and error rehearsals in the classroom for novice modelers, and the lack of validation procedures and tool support (Sedrakyan et al. 2014). Verbruggen and Snoeck's (2021) meta-review reports that in the Model-Driven Engineering approach to IS engineering (where CM prevails), the most critical problems are the high effort required to acquire skills (e.g., practical use of modeling languages), in addition the high effort required to use the tools that often rely on visualization of the models. Research such as Panach and Pastor (2023) aims to address this issue by proposing relevant course designs to tackle students' modelling and abstraction skills.

Didactical challenges are not limited to the field of IS engineering, however: constructing, testing, and refining models of the physical world is a core practice in science research and constitutes the core of the process of modeling (Etkina et al. 2006; Schwarz et al. 2009). For instance, chemistry and physics utilize atomic models, whereas technology and engineering use conceptual and physical models. Models can serve as a bridge between the disciplines in the STEM field, which are epistemologically different but closely related to scientific and engineering practice. Such bridging must not be perceived merely as mergers but as interdisciplinary cooperation on equal terms (Gilbert et al. 2000; Hallström and Schönborn 2019).

2 Research Gaps, Objectives, and Questions

Based on the above discussion, we identify two pertinent *Research Gaps (RGs)*

RG1 Despite the common ground across different CM subfields and subtypes, a lack of shared knowledge and understanding still exists. At the same time, recent literature formulates a call for cross-disciplinary research in CM.

RG2 Educational research on CM is still limited and fragmented. Because of insufficient interdisciplinary research, researchers within a particular CM subtype (e.g., process or data modeling) cannot sufficiently incorporate and validate findings of pedagogical approaches from other CM subtypes.

To contribute to closing these research gaps, this study's guiding Research Objective (RO) is *"to investigate CM educational research in different fields of expertise to promote cross-fertilization, external validity, and transferability of the findings across the CM subtypes education."*

We will delimit the selected papers only to those pertaining to education or learning in some manner, providing analysis from the perspective of the broader CM education field. To the best of our knowledge, there is no current organizing overview of the literature on connecting the topics in the CM education field, as seen from the proposed broader perspective on CM. We will adopt an extensive literature review combining a bibliometric literature analysis with a semi-automated content analysis to achieve the research objective. Bibliometric literature reviews are a well-suited methodology to provide a broad account of a given domain, exploring the underlying conceptual, social, and intellectual structures (Aria and Cuccurullo 2017). Semi-automated content analysis allows us to understand the CM education field's research methods, contexts, learning theories, and approaches to draw systematic conclusions. This allows us to analyze and propose research gaps and future directions in CM education using bibliometrics.

Accordingly, we define the following *Research Questions (RQs)*:

RQ1 How can the subtypes of CM education be characterized in terms of research methods, contexts, learning theories, and approaches?

RQ2 What is CM education literature's conceptual structure (the topics and tendencies)?

RQ3 What is CM education literature's social structure, i.e., the recurring countries, authors, and their collaboration?

RQ4 What is CM education literature's intellectual structure, i.e., the most cited articles, publishing outlets, and emerging research topics?

The rest of the paper is structured as follows. In the next section, we introduce the methodology and the data extraction process. Then, the analysis results are presented, outlining in the CM education field the employed research methods, contexts, learning theories, and approaches, the conceptual structure, the social structure of researchers, and the most influential publishing outlets, articles, countries, and authors across the CM subtypes. Next, we discuss the results and future research directions for the CM education field. Finally, we present a discussion of limitations and a conclusion.

3 Previous Reviews on Conceptual Modeling and its Education

Only a few related overview articles address the CM field or CM education as understood *broadly*. Prior work reviewing the more general topic of CM and proposed research agendas only rarely or implicitly discuss teaching and learning CM: In their fundamental work, Wand and Weber (2002) suggest a research agenda comprising topics that address the essential question of "How can we model the world better?". Several research opportunities related to modeling languages, methods, models, and modeling context are discussed. However, teaching and learning CM is not explicitly mentioned in the future research directions. Fettke (2009) presents the results of a web survey among modeling practitioners to inform about CM use in practice. An overview of modeling techniques and tools used in practice shows that their usage has increased with a focus on only a few widely used techniques and tools. The results are, among other things, intended to serve as a basis for designing courses on CM, linking to curricula and course design in CM education. The elements of a research agenda suggested by Frank et al. (2014) focus on a pluralistic approach to CM research and integrating knowledge from related research fields. With regard to transferring research results to business practice, conceptual modeling education is mentioned as one means by which relevance should not be underestimated for distributing and adopting research findings.

In Sandkuhl et al.'s (2018) "From expert discipline to common practice," a vision for extending the scope of enterprise modeling to the application by stakeholders across entire organizations is elaborated, focusing on how people use models for their practice. However, the learning and teaching of CM are not explicitly mentioned. A more recent bibliometric review by Härer and Fill (2020) covers a period from 2005 to 2019 and analyses over 3000 papers on the evolution of research topics. The results show that the primary focus in CM is on the technical, fundamental aspects of modeling and schemas (e.g., metamodels, transformations constraints, and schemas) and process and business modeling topics, with software and data models being slightly less popular. Learning and teaching CM is not identified as a research theme (Härer and Fill 2020).

Recker et al. (2021) limit their review to CM in Information Systems (IS) research, excluding progress made in other fields such as, for example, model-driven engineering. The review acknowledges the relevance of CM for IS and calls for an update of CM theory. Within their work, learning and teaching CM is recognized as a context where CM is applied, but it is not explicitly mentioned in the proposed framework for CM.

A recent large-scale literature review of over 5000 papers, again focusing on IS research, surveys research on conceptual modeling on topics and trends, proposing future research directions to strengthen the role of CM in the digitalized world (Storey et al. 2023). The review does not find education a frequent topic in CM literature. However, in the context of broadening the user base of CM, Storey et al. (2023) suggest improving the process of developing, deploying, and learning conceptual modeling as a relevant future research direction. Prior review research on CM education is also found rare within the study of Rosenthal et al. (2019), providing a structuring overview of the literature on learning and teaching CM restricted to "core" CM, i.e., process, data, object-oriented, and conceptual modeling education. The review considers learning paradigms and identifies learning tool support, feedback, learning analytics, and gamification/serious games as prevalent and emerging research themes.

Further related overview articles in the field of CM education have different and narrower foci: Börstler et al. (2012) review how Computer Science and Software Engineering curricula approach the topic of software modeling. Based on the results, recommendations on including software modeling courses in curricula are provided. Agner and Lethbridge (2017) also address software modeling but focus on the use of modeling tools. Surveying educators in software engineering leads to an overview of over 30 modeling tools that are analyzed, including motivations for choosing the tools and challenges in their application, e.g., regarding limited modeling support and complexity. A more recent literature review addresses the topic of automated assessment of conceptual models (Ullrich et al. 2023). A systematic analysis provides an overview of the current state of the art of assessment approaches and techniques for conceptual models and the accompanying teaching and learning settings. The authors discuss connecting automated assessment systems with educational theories and CM competencies as one central path for future research.

Altogether, prior meta-research on CM and its education only mentions teaching and learning CM as one (minor) point in the broad field of CM or focuses on a specific aspect of education, such as modeling tools or assessment of conceptual models. Hence, a systematically consolidated knowledge base from the perspective of the broader CM education field is missing at present.

4 Methodology

This paper presents a bibliometric literature review, blending bibliometric analysis with semi-automated content analysis through automatic keyword tagging. We first established the research scope to formulate the search string, followed by acquiring and filtering relevant papers. A standard bibliometric analysis was then conducted, supplemented by semi-automatic content analysis using keyword tagging.

Bibliometric methods allow literature review and evaluation by identifying intellectual mapping, gap analysis, journal rankings, institution rankings, country collaboration analysis, country scientific specialization, and personal evaluations (Zupic and Cater 2015; Glänzel 2003). Bibliometric methods can be performed across conceptual, social, and intellectual structures. Conceptual structure reveals the subject matter and prevailing trends in a particular domain. Social structure analysis indicates how authors, institutions, and countries interact with each other based on co-authorship. The intellectual structure shows how an author's work influences the scientific community (Aria and Cuccurullo 2017). We have employed the five bibliometric methods (Zupic and Cater 2015) – citation, co-citation, bibliographic coupling, co-author, and co-word analysis – since combined, they contribute to a wholesome and balanced picture, thus allowing for triangulation of the results (Saunders et al. 2009). Furthermore, we follow Zupic and Cater (2015), proposing a 5-step process for conducting a bibliometric literature review (research design, data compilation, analysis, visualization, and interpretation). Next to conventional bibliometrics, we also employ the automatic keyword tagging method of bibliometric data (Thushara et al. 2017) as a complementary method to improve the richness of the bibliometrics (Zupic and Cater 2015). Keyword tagging is an approach that allows for analyzing and categorizing literature samples (Krippendorff 2019). Assigning identification tokens to research papers facilitates the analysis of the themes in the content by quantification means (Thushara et al. 2017).

5 Research Design Steps

The research design steps included 10 stages (Fig. 1), including search string construction, literature retrieval stages, and the associated analysis (bibliometrics and keyword analysis) at the final stages. Two to four rounds of iteration were applied in the initial four stages.

5.1 Scope Delimitation and Inclusion and Exclusion Criteria

The first exploratory phase discussed relevant conceptual and generic modeling subtypes with their modeling purpose/target (Table 1) and defined the inclusion and exclusion criteria (Table 2). Two major dimensions were considered for inclusion: (1) CM subtype domain application and the nature of the subtypes, and (2) the educational focus of the research. Note the use of the CM subtype initials in the data analysis tables.

We assume that CM subtypes are understood as conceptual- and abstraction-building processes, typically (but not always) using visual diagrams. As the foundation of our research, we started from what can be considered the heart of CM (Härer and Fill 2020; Rosenthal et al. 2019) and extended it with modeling practices in information systems engineering (Laudon and Laudon 2021). As a result, we designate eight CM subtypes: conceptual, software (IS), data, business, enterprise, (business) process, and data modeling as our focal point and call it the 'core CM' in the following.

Given the research objective of considering broader CM, we designate five CM subtypes situated in a different domain closely related to core CM. Such a delimitation is worthwhile as the transfer of educational implications is more valid across closely related CM subtypes. To delimit, we considered their idiosyncratic similarities in externalizing implicitly contained conceptual structures, usually in the form of visual, conceptual models, or their direct relevance to describing such a process (like mental and meta-modeling). Hence, we included science modeling, mental modeling, meta-modeling, domain and ontology modeling, educational modeling languages, and ecological modeling.

To establish clear boundaries, we excluded numerical and quantitative-driven modeling, as in simulation, computational, mathematical, agent-based, economic, finance, technical modeling (like in construction, 3D, or geographical modeling), and modeling that is not based on core CM defining characteristics (role and citizen modeling). They focus on a concrete representation of a highly idiosyncratic reality or phenomenon, trying to explain it as realistically as possible (Mylopoulos 1992). We decided to exclude them, given that CM is more focused on externalizing implicit mental models and not per se on explaining a particular phenomenon as realistically as possible. We excluded these 11 modeling types from the search string but explored whether they co-occur with included CM subtypes. Science and ecological modeling were included due to their inherent emphasis on concepts rather than mathematics (Couclelis 2002; Taber 2013). Note further discussion on the issue in Sects. 5 and 7.

We exclusively incorporated papers explicitly dedicated to enhancing the expertise and proficiency of modelers. Additionally, we integrated papers that we considered highly pertinent, even if they indirectly affected the skills of CM modelers. These indirect influences encompass research on software utilized by CM modelers and efforts to enhance CM instructors' skills. Papers had to be written in English, and tutorials and guides were excluded.

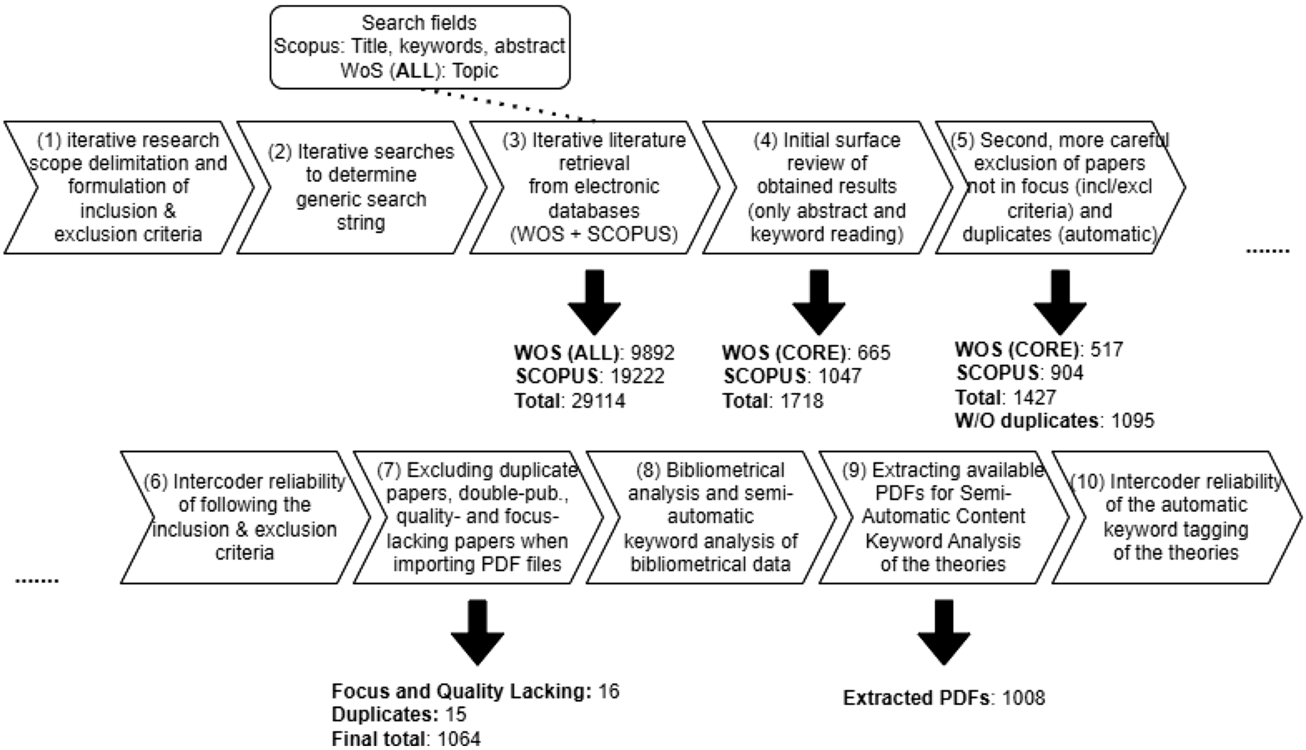

Fig. 1 Research design steps

5.2 Iterative Search String Construction

We adapted the search strings applied in Moreno et al. (2015), Rosenthal et al. (2019), and Härer and Fill (2020) for our purposes. We first researched relevant keywords by going through available literature. Following the advice of (James Cook University 2023), we checked for different spellings, tenses, and word variants of keywords, synonyms, and related concepts using the Oxford dictionary. Proximity operands NEAR/ (for Web of Science) and W/ (for Scopus) were used instead of AND or OR to limit the number of hits and increase feasibility. Exhaustiveness can never be guaranteed for a literature review (vom Brocke et al. 2015). Thus, we stopped the iterative process when adding new keywords did not bring any new relevant results.

The final search string is below. It addresses three parts: ([*pedagogy and education keywords*] **NEAR/3** ([*CM subtype*] **NEAR/2** [*modeling*])). The pedagogy and education keywords can be within 3 keywords of the CM subtype and modeling, which can be within 2 words from each other when merged.

("teach" OR "instructing" OR "coaching" OR "upskilling" OR "practicing" OR "guid*" OR "preparing" OR "behavio?r" OR "educat*" OR "instruct*" OR "learn*" OR "prepar*" OR "exercis*" OR "guid*" OR "lesson*" OR "knowledge" OR "skill*" OR "pedagog*" OR "curricul*" OR "syllab*" OR "stud*" OR "train*" OR "tutor*" OR "feedback" OR "assess*" OR "literac*" OR "course" OR "experience" OR "MOOC" OR "apprentice*" OR "competence*" OR "learning environment")* ***NEAR/3*** *(("object" OR "mental" OR "research*" OR "scien*" OR "UML*" OR "Software" OR "Model?-Driven Development" OR "MDD" OR "Model?Driven Engineering" OR "MDE" OR "BPMN" OR "BPML" OR "EPC" OR "EML" OR "Educational Modeling Language?" OR "RAD" OR "Activity diagram?" OR "BPEL" OR "TOGAF" OR "YAWL" OR "ZACHMAN" OR "KAOS" OR "ITML" OR "TBIM" OR "archimate" OR "ORM" OR "Object?Relational?Mapping" OR "*goal" OR "user requirement? notation" OR "goal?oriented requirement? language" OR "use case maps" OR "UCM" OR "URN" OR "GRL" OR "EEML" OR "ADL" OR "SOMF" OR "ontolog*" OR "ARIS" OR "DS??" OR "SDL" OR "OWL" OR "LINGO" OR "CIMOSA" OR "IDEF*" OR "ADeL" OR "meta" OR "e?3?value" OR "use case? diagram?" OR "user stor*" OR "canva?" OR "petri?net?" OR "class diagram?" OR "sequence diagram?" OR "flow chart*" OR "database" OR "conceptual" OR "semantic" OR "entity?relationship" OR "domain" OR "ER" OR "enterprise" OR "process" OR "business process" OR "logico?linguistic" OR "state transition" OR "business" OR "workflow" OR "data" OR "data?flow" OR "object?role" OR "object?oriented" OR*

Table 1 CM subtype categories and associated keywords

CM subtype	Initials	CM subtype modelling purpose/target	Associated Keywords
Core CM subtypes			
Information Systems Modelling	ISM	Software and information systems	"UML", "Unified modeling language?", "Software model*", "Model?Driven Development", "MDD", "Model?Driven Engineering", "MDE", "use case? diagram?", "data?flow", "object?role", "object?oriented", "OO", "OOP", "class diagram?", "sequence diagram?", "RAD", "state transition", "ADL", "SOMF", "ARIS", "IDEF*", "state machine diagram?", "software model* tool?", "software engineering", "software process model*", "algorithmic model*", "requirement*model*"
Data Modelling	DM	Data structures and databases	"Object model*", "data model*", "Object?Relational?Mapping", "data?flow model*", "object?role", "object?oriented model*", "OO", "OOP", "ORM", "Visio", "FAME", "RDF", "database model*", "ER", "entity?relationship", "relational database schema"
Domain & Ontological Modelling	DOM	Domain and ontology	"domain", "ontolog*", "OWL", "ADeL", "logico?linguistic", "semantic model*"
Conceptual Modelling	CM	Generic and domain-specific conceptual modelling	"canva?", "conceptual model*", "DSML", "FAML", "soft systems", "SDL", "LINGO", "domain?specific", "DSL"
Process Modelling	PM	Business and organization processes	"BPMN", "BPML", "EPC", "Activity diagram?", "BPEL", "YAWL", "UML*AD", "petri?net?", "Signavio", "ARIS", "ADONIS", "DMN", "CMMN", "workflow model*", "flow chart* model*", "business process model*", "process model*", "business process management?", "Business process model and notation"
Enterprise Modelling	EM	Enterprise and its structure	"archimate", "enterprise?model*", "BMM", "TOGAF", "ZACHMAN", "KAOS", "ITML", "TBIM", "SoaML", "EEML", "SOMF", "CIMOSA"
Business Modelling	BM	Business organization	"SBVR ", "canva?", "e?3?value", "business model*"
User Modelling	UM	Users and their goals	"goal model*", "user requirement? notation", "goal?oriented requirement? language", "use case maps", "UCM", "URN", "GRL", "user stor*", "use case? diagram?"
Distantly relevant to core CM subtypes			
Science Modelling	SM	Multiple domains in science (e.g., physics, chemistry, biology)	"Research model*", "scien* model*", "model?based inquiry", "MBI", "science education", "chemistry", "physics", "biology", "biomechanics", "Scien*reasoning", "scien*", "scien* instruction", "scient* knowledge*", "geolog*"
Mental Modelling	MenM	Implicit conceptual structures	"Mental model*", "cognitive model*", "model?based reasoning", "meta?cognitive"
Meta-Modelling	MetM	Generating meta-model to create conceptual models	"Meta*model*", "ADoXX"
Ecological Modelling	EcoM	Ecology	"ecologic* model*", "eco*model*", "ecosystem"
Educational Modelling	EduM	Educational process	"EML", "Educational Modelling Language?", "Competency model*"
Potentially relevant but excluded modelling types			
Mathematical Modelling	MatM	Mathematical structures	"Mathematical model*", "neural network?", "data analytic?"
Simulation Modelling	SimM	Running simulations on the preset models	"Simulation model*", "agent?based model*", "computer?based model*", "simulation", "ABM", "NetLogo", "computational model*"
Computational Modelling		CompM	Using computers to simulate complex systems
		"Comput*model*"	
Agent-Based Modelling	ABM	Computer simulations of "agent" entities	"ABM", "agent-based", "NetLogo"
Learner & Student Modelling	LSM	Student and learning processes and behaviour (mathematically)	"Student model*", "Learner model*"

Table 1 continued

CM subtype	Initials	CM subtype modelling purpose/target	Associated Keywords
Technical Modelling	TM	Technical simulation of concrete objects	"BIM", "3D", "CAD", "CAM", "mechanics", "technical object*"
Role Modelling	RM	People simulating other people's behaviour as a social phenomenon	"Role*model*"
Geographical Modelling	GM	Technical representation of geography	"GIS", "GPS"
Economic Modelling	EconM	Economics	"Economic model*"
Finance Modelling	FM	Finances	"Finance model*"
Citizen Modelling	CitM	(Quasi-)scientific citizen models	"citizen"

Table 2 Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Completely or substantially written in English and about one or several of the following:	Not meeting the inclusion criteria, and:
teaching or learning (and synonyms), the skills or knowledge of CM subtypes	tutorials or guidelines to using CM subtypes,
using (modelling) tools within a CM education context,	mathematical-oriented types of modelling (like mathematical, finances or economic modelling),
potential theoretical and practical implications to teaching CM (e.g., studying the process of PM and PM comprehension),	technical-leaning types of modelling (like computer assisted design or 3D modelling),
a technique or a method used in the context of teaching or learning CM (e.g., software to analyse the semantics of course discussion in CM course)	computer or simulation modelling,

"OO" OR "OOP" OR "soft systems" OR "DMN" OR "CMMN" OR "ADoXX" OR "Signavio" OR "Visio" OR "ARIS" OR "ADONIS" OR "FAML" OR "FAME" OR "SoaML" OR "BMM" OR "SBVR" OR "RDF") ***NEAR/2*** *("mode?ing")).*

5.3 Literature Retrieval and Filtering for Relevancy

We focused on Web of Science (WoS) and Scopus, two widespread and comprehensive bibliographic databases. Scopus has a broader coverage in general, whereas WoS has a higher coverage of economics and business (Joshi 2016; Aria and Cuccurello 2017). After defining the scope (step 1) and using the search string (step 2), we obtained 29,114 search hits (step 3). Using the inclusion and exclusion criteria, we went through this list at a surface level by looking at titles and abstracts and automatically searching for highlighted and color-coded keywords in the webpage of the results (e.g., 'student' was highlighted green, 'modeling' yellow, etc.), and managed to limit the number of papers to 1718 across the two databases (step 4). We then filtered again via a more rigorous approach, using titles, abstracts, and parts of the text, and got 1427 documents, or 1095, after excluding duplicates across the two databases (step 5). Finally, we manually extracted PDFs and excluded 31 duplicates or low-quality papers (step 7). The final number of the papers used in the bibliometrics analysis is 1064.

As a reliability check, a 3-stage procedure was applied by the 3 researchers to establish intercoder reliability based on title, abstract, and author keywords.

1. After initial surface-level filtering of 29,114 documents, the set of 1718 documents was subdivided into 3 equal sets of appr. 570 documents were assigned to the 3 researchers. A decision was made for each paper: include, exclude, or doubtful.
2. Each researcher was then assigned a different lot of 100 papers (50 from each of the other two researchers), with previous decisions concealed. This step included a new round of assessments, resulting in 300 papers receiving dual evaluations.

3. Researchers reevaluated 100 papers from step 2, considering dual assessments to make a final decision.

The ICR (Table A.1 in the appendix) ranged between 81 and 86% in stage 2 and between 90 and 92% in stage 3. These results can be considered a quasi-consensus on the inclusion and exclusion of papers (Cheung and Tai 2021).

We compared the results of the current literature retrieval process with the dataset obtained through a retrieval effort for systematic literature on the topic of learning and teaching "core" CM, or process, data, IS, and conceptual modeling education (Rosenthal et al. 2019). A literature retrieval that employed backward and forward search resulted in 121 papers, out of which 94 were found in the Scopus database. Of these 94 papers, 28 were not found in our dataset. Despite this, the parallel dataset did not cover all the papers in our broader dataset. We were considering the typical scope of literature reviews in CM and CM education, which ranges from about 100 to several thousand papers, as discussed in sources like (Härer and Fill 2020; Recker et al. 2021; Storey et al. 2023; Rosenthal et al. 2019). Our results, while imperfect, still represent a substantial collection of pertinent studies. This suggests that, although there is room for improvement, our retrieval process successfully captured a significant sample of relevant literature.

5.4 Bibliometrics and Automatic Tagging of Bibliometric Data and Document Content

After the data collection and filter stages and establishing ICR, we performed the bibliometrics analysis using Bibliometrix, an academically validated R-language library (Aria and Cuccurullo 2017). We applied the following analysis: bibliometric data statistics overview; most relevant authors, articles, sources, and institutions; scientific production of countries; authors' keyword analysis; authors' collaboration network; authors' co-citation network; conceptual structure perceived through a thematic map and authors' keyword co-occurrence. For reasons of brevity, several tables and visualizations are provided in the online appendix (Tables and Figures denoted with the letter A before the number), as they are supplementary to the conclusions of the presented analysis. (The appendices are available via http://link.springer.com).

We used an R script (attached to Appendix) to assign keywords belonging to three categories: CM subtype (Table 1), research method (Table A.2 in the appendix), and research context (Table A.3). We coded using bibliometric data: title, abstract, and author keywords. The keyword/category schemas of CM subtypes can be found in Table 1, and for research context and method, we used an adapted version of Recker et al. (2021). Research context refers to the targeted population (e.g., K-12 or university-level), and research methods encompass typical approaches (e.g., case study, survey, experiment). Several keywords of multiple categories may be assigned to the same document to analyze their co-occurrence. Approximately 96% of documents were tagged with one or more CM subtypes, and 64% and 56% were tagged with a research method and context, respectively (Table A.4). Authors reviewed the coding scheme several times, the percentage of documents assigned with a keyword tag. The assessment revealed that automatic coding led to about 15% inaccuracies in CM subtype assignments and 30% for research method and context, encompassing false positives and false negatives.

We also performed within-document semi-automatic content analysis by assigning categories of often-used learning theories and approaches (Wu et al. 2012; Rosenthal et al. 2019). We decided to take this approach since the bibliometric data (including titles, abstracts, or author keywords) did not mention enough information on the learning theories. We assigned theories to the documents that we succeeded in downloading (1008 out of 1064) via the search query coding of NVivo, a qualitative and quantification analysis software. Each text had a keyword frequency number referring to a given theory. Consequently, each author reviewed 50 random documents and found that if a text mentioned a keyword at least 3 times, then 90% of these documents are relevant (i.e., a theory is meaningfully impacting the study and not used as a counterargument, or only in the referenced literature titles). Approximately 30% of the papers were thus tagged with at least one learning theory category using a cut-off value of 3 or more keywords. It is typical for CM education studies not to mention explicitly learning theories (Rosenthal et al. 2019), hence a low percentage of target papers.

6 Data Analysis Results

This section presents the results of the data analysis. Note that for reasons of brevity, we only present the major findings. More detailed findings are presented in the supplemented appendix containing figures and tables.

6.1 Initial Data Statistics

Our data sample covers 1064 papers from 1982 to 2023 across 24 modeling subtypes (Fig. 2). On average, the annual production from 1982 to 2022 is about 26 articles per year. The median age of documents is 8, meaning that between 1982 and 2015, there were as many documents as between 2015 and 2023. The CM discipline is older (starting from the 1970s) than CM education (1980s). Proportionally, the importance of CM education (note

Table 3 Clusters of author keywords co-occurrence

#	Modelling type	Associated (learning) topics, concepts and methods	**Freq**
1	Data and conceptual modelling	Pedagogy; database design; modeling tool; visualization; ontology; empirical study; prototyping; model driven development; database	116
2	Computational Modelling	Computer Science Education; Model-based reasoning; educational technology	27
3	Science and conceptual modelling	Simulation; engineering education; information systems; systems thinking; data analysis; inquiry; problem solving; argumentation; nature of science; programming; science teaching	232
4	Conceptual, data, software (IS), enterprise modelling	UML; software engineering education; e-learning; gamification; assessment; higher education; software design; scaffolding; formative assessment; instructional design; object-oriented analysis and design; blended learning; collaborative modeling	246
5	Agent-based modelling	Science education; computational thinking; conceptual change	42
6	Scientific modelling	Scientific practice; water	43
7	Process modelling	bpmn; business process management; bpm; experiment	86
8	–	Model-based learning and inquiry	13
9	Class and Sequence diagram modelling	Abstraction	23
10	–	Collaborative and project-based learning	15
11	Process modelling	Active learning	14

Table 4 Conceptual thematic clusters according to CM subtypes and learning topics

#	Modelling topics	Learning topics	Theme Type	Freq
1	Conceptual, software, IS, UML, data, chemistry, enterprise, ER, OOP, model-driven development	E-learning, CS education, feedback, Edtech, formative assessment, instructional design	Motor	307
2	Science and mental modelling	Model-based learning, experiental learning, model-based inquiry, nature of science, argumentation	Niche / Motor	112
3	Class and sequence diagram	NA	Niche	23
4	Enterprise and conceptual modelling	Modelling tool and prototyping	Niche	26
5	Scientific modelling	Intelligent tutoring systems, scientific practice, physics education	Emerging or Declining / Niche	50
6	–	Modelling-based learning	Emerging or declining	6
7	(Business) process modelling	Gamification, experimentation	Basic	82
8	Data, database, process, ontology, modelling, model-driven engineering	Assessment, collaborative learning, engineering education, visualization, active learning, higher education, project-based learning	Basic	123
9	Simulation, computational modelling, agent-based modelling	Science education, computational thinking, systems thinking, conceptual change, learning strategies, model-based reasoning, programming	Basic	193

broader conceptualization in this dataset) in the CM field has become apparent only recently: before 2015, there were about 10 times more papers produced in core CM every year than in CM education, and after 2015, there were about 2 to 5 times more publications (Storey et al. 2023). The dataset comprises 454 journal articles, 563 conference papers, 31 book chapters, 13 reviews, 1 book, 1 note, and 1 editorial paper. We identified 601 publication outlets 2046 authors, and 2244 unique author keywords. There are about 10% international co-authorships and an average of 3 co-authors per document. Note that some publications of 2022 were not yet indexed at the time of the final search string (early 2023). Hence, we observed a drop in 2022. The total publications in 2023 are excluded due to the lack of information (with only 6 publications that year). The sub-types will be further discussed in the following section.

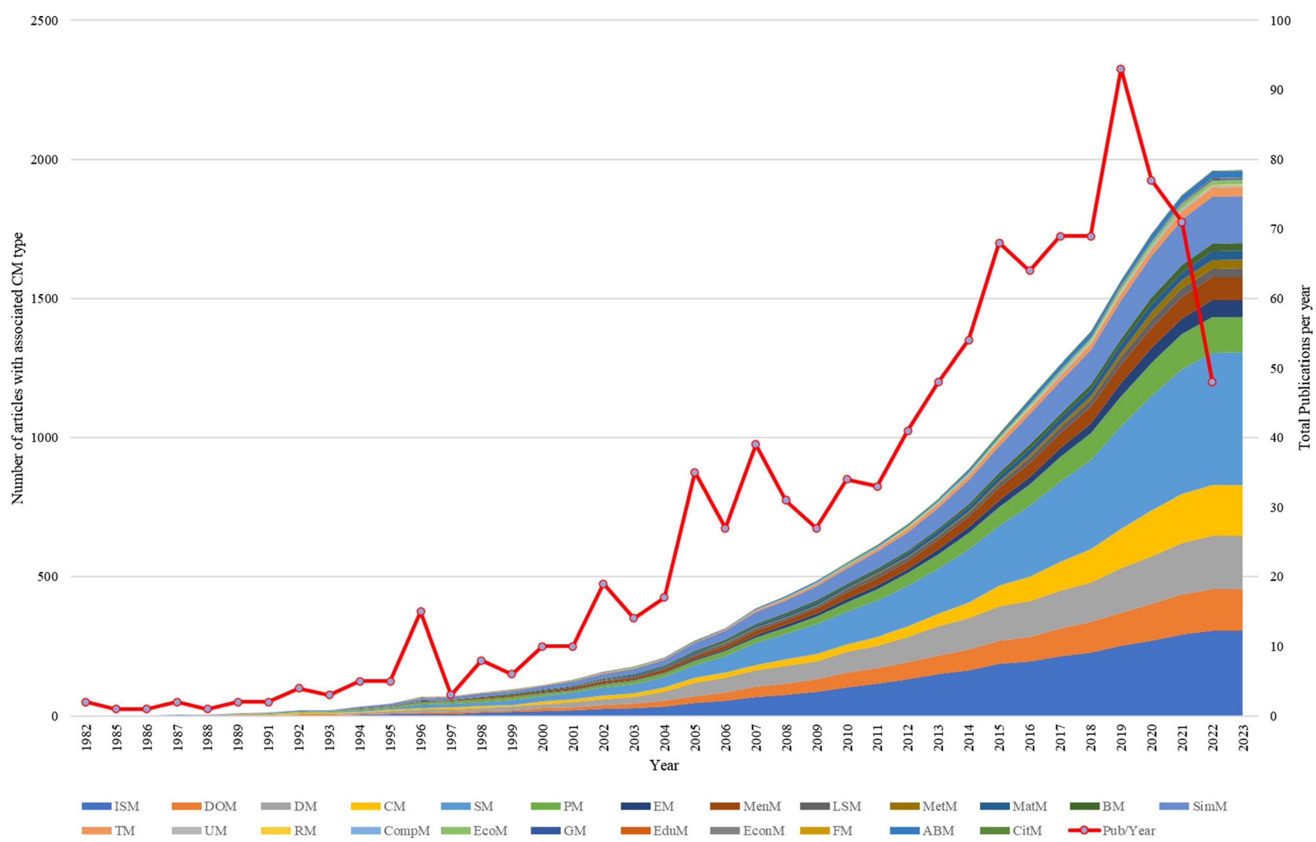

Fig. 2 Cumulative number of publications per CM subtype and total publications per year (red line)

6.2 CM Subtypes

There are 1956 subtypes across 1064 papers, with an average of 1.83 per study (Fig. 2). The most frequently studied subtypes include science (486 documents), IS (300), data (189), conceptual (188), simulation (164), domain and ontological (151), and process modeling (127). CM subtypes that were included extensively in the search string but had fewer than 100 documents are enterprise (58), business (25), user (9), mental (82), meta- (34), and ecological (15) modeling. Compared to what we defined as the core subtypes (enterprise, business, and user modeling), science modeling is overrepresented in the sample. Furthermore, we observe that meta- and mental modeling and ecological modeling (designated as distantly related subtypes) are underrepresented.

In contrast, we observe many modeling types that are frequently co-occurring, although excluded in the search string: mathematical modeling (33), simulation (164), technical (29), and agent-based modeling (25), indicating a high interest and relevancy of these modeling types. This is not surprising as, for instance, business processes being modeled as conceptual models can be simulated via mathematical and simulation modeling for informed decision-making (e.g., Dumas et al. 2018) and learning these can become crucial.

To explore the structure in more detail, we employ a co-occurrence matrix heatmap across the CM subtypes (Fig. 3). We observe a clear co-occurrence of the topics within the core CM. Solid co-occurrence connections exist between data and IS modeling, CM, and domain/ontology modeling. Core CM can thus be considered a single coherent cluster. Of the non-core CM subtypes, we find co-occurring simulation and agent-based modeling with science and ecological modeling, which can simulate complex conceptual systems (e.g., Couclelis 2002). Science modeling generally seems more integrated with distantly related and excluded modeling types, such as with technical, hinting at its potential "borderline nature," but also possibly due to the larger volume of science modeling education publications. Science modeling also seems to have higher co-occurrence with "technical core CM" (e.g., data modeling) than with "business core CM" (e.g., process modeling), which, according to numbers, is about the same as co-occurrence within core CM. Mental modeling is most developed through science modeling but not through other types of modeling, potentially represented by the topics of modeling-based learning of science and modeling learners' conceptual understanding of science topics (Taber 2013).

	ISM	DM	DOM	CM	PM	EM	BM	UM	SM	MenM	MetM	EcoM	EduM	MatM	SimM	CompM	ABM	LSM	TM	RM	GM	EconM	FM	CitM
ISM	300																							
DM	93	189																						
DOM	49	31	151																					
CM	57	41	70	188																				
PM	31	13	20	13	127																			
EM	17	7	17	16	14	58																		
BM	7	2	3	6	7	3	25																	
UM	6	2	1	3	0	0	0	9																
SM	65	47	43	57	25	15	9	2	486															
MenM	9	8	6	10	2	1	1	0	52	82														
MetM	11	3	11	15	5	5	0	0	20	0	34													
EcoM	1	0	1	3	0	0	1	0	10	0	0	15												
EduM	0	1	0	0	0	1	0	0	1	0	0	0	2											
MatM	6	5	4	1	2	3	1	0	18	3	0	0	0	33										
SimM	22	6	20	31	17	12	5	0	91	11	4	2	0	5	164									
CompM	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2								
ABM	3	1	5	3	0	2	1	0	18	1	1	1	0	0	23	0	25							
LSM	5	1	9	4	2	1	1	0	12	2	1	4	0	0	4	0	0	28						
TM	4	3	2	2	2	0	0	0	18	2	0	0	0	1	6	0	0	0	29					
RM	1	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1				
GM	0	1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	4			
EconM	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1		
FM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
CitM	0	0	0	0	1	0	1	0	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	3

Fig. 3 Co-occurrence heatmap of CM types in the CM education field

6.3 CM Research Methods

We perform a co-occurrence heatmap analysis of CM subtypes and research methods (Fig. 4). We find that experiments, design science, course design, survey, interview, and case studies are among the most frequently used research methods in CM education, used in several subtypes. Quantitative research methods are noticeably less abundant compared to qualitative methods. We only observe in exceptional (rare) cases the use of physiological methods (such as fMRI, EEG, and eye-tracking). However, such methods have the potential to contribute to a more comprehensive picture of the process of modeling, complementing more interpretative qualitative methods. The finding is in line with Batista Duarte et al. (2021), who, for instance, observed an apparent lack of eye-tracking in exploring how process model comprehension relates to the learning of Process Modeling. There is also a lack of longitudinal, non-empirical, and theory-building research (only 13 literature reviews). Almost all observed research methods have been used in science modeling, which can be attributed to the maturity of this domain (see Sect. 4.5) and the fact that Science Modeling is the most frequent CM type in our sample.

6.4 CM Research Context

On the co-occurrence heatmap analysis of research contexts and CM subtypes (Fig. 5), we observe a strong tendency in the sample to conduct research in the context of higher education. Next, vocational training is also a frequent research context, followed by high school (including middle school). We further note a relative lack of research within the context of PhD, primary school, and teacher training. Citizen science is a relatively recent phenomenon, occurring only 10 times in our dataset, and it can be broadly defined as the active involvement of non-professional individuals in (quasi-)scientific endeavors (such as data collection, analysis, and problem-solving). For example, they can be asked to collect photos to help develop geographical IS (Storey et al. 2023).

Science, simulation, agent-based, mental, meta-, and mathematical modeling are studied equally throughout all levels of education (except the PhD level). However, the core of CM is studied more in higher education contexts and less so in an industry or vocational context. Citizen science is only taught in the context of science, process, mental, business, simulation, and citizen modeling.

	ISM	DM	DOM	CM	PM	EM	BM	UM	SM	MenM	MetM	EcoM	EduM	MatM	SimM	CompM	ABM	LSM	TM	RM	GM	EconM	FM	CitM	Total:
Case Study	25	14	13	13	17	8	4	0	43	10	5	1	0	3	18	0	4	3	0	0	0	0	0	2	183
Action Research	1	0	0	0	3	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
Survey	31	20	3	14	9	7	4	1	57	4	5	0	0	3	9	0	1	0	6	0	0	0	0	1	175
Interview	10	9	3	5	4	10	4	0	49	12	1	1	0	1	16	0	2	0	4	0	0	0	0	1	132
Panel	1	0	0	1	0	0	0	0	1	1	0	0	0	0	2	0	0	1	0	0	0	0	0	0	7
Delphi Study	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Experiment	51	34	23	35	25	6	3	2	82	20	5	2	0	10	35	0	4	5	5	0	0	0	0	1	348
Design Science	65	37	21	33	12	6	4	0	35	2	4	2	0	1	15	0	1	2	1	0	1	1	0	1	244
Literature Review	0	0	0	2	4	2	2	0	6	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	19
Theory Development	4	4	4	7	0	4	2	0	24	3	1	1	0	2	6	0	1	1	2	0	0	0	0	0	66
Commentary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thinking Aloud	0	1	0	1	1	0	0	0	5	2	0	0	0	0	1	0	0	0	1	0	1	0	0	0	13
Focus group	1	1	1	1	1	1	1	0	6	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	17
eye tracking	0	0	0	0	4	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
fMRI / EEG / brain scanning	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2
Observation	12	10	7	17	10	4	3	0	29	6	1	0	0	4	7	0	2	0	3	0	0	0	0	1	116
Assignment	13	10	4	6	4	7	1	1	19	1	0	0	0	1	6	0	0	3	2	0	0	0	0	0	78
data analytics	2	1	5	4	3	2	0	0	5	0	0	1	0	4	2	0	1	3	0	0	0	0	0	0	33
Longitudinal	0	2	0	1	0	0	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
Course design	56	31	13	27	15	9	6	0	45	4	0	0	0	7	17	0	1	1	2	0	0	0	0	0	234
Empirical	29	22	16	27	14	4	2	1	39	7	2	0	0	3	9	0	1	1	3	0	0	0	0	2	182
Non-empirical	1	0	0	0	3	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	7
Teaching Experience	4	2	2	3	3	1	1	0	6	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	25
Mixed methods	3	3	0	2	0	1	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14
Qualitative analysis	15	4	9	8	6	2	2	0	48	14	3	2	0	2	16	0	1	2	4	0	1	0	0	1	140
Quantitative analysis	6	5	1	7	2	1	0	0	17	4	0	2	0	1	11	0	1	1	4	0	0	0	0	0	63
Learning analytics	1	1	3	5	0	1	1	0	4	0	0	2	0	1	0	0	0	3	0	0	0	0	0	0	22
Teaching guide	16	12	9	10	9	4	2	1	11	0	2	0	0	0	10	0	0	2	1	0	0	0	0	0	89
Total:	347	223	137	229	149	82	44	6	545	93	29	16	0	46	183	0	20	29	38	0	3	1	0	11	

Fig. 4 Co-occurrence heatmap of the CM types and research method (NOTE: totals count for the CM types that may have multiple types associated with a single document)

	ISM	DM	DOM	CM	PM	EM	BM	UM	SM	MenM	MetM	EcoM	EduM	MatM	SimM	CompM	ABM	LSM	TM	RM	GM	EconM	FM	CitM	Total:
Primary school	5	10	7	6	4	1	0	0	50	6	2	3	1	4	8	0	2	1	1	0	1	0	0	0	112
Middle school/high school	13	14	8	10	5	5	1	0	85	11	8	2	0	3	20	1	2	5	1	0	1	0	0	0	195
High school	15	9	10	10	4	1	0	0	59	11	4	2	0	2	14	0	4	1	4	0	0	0	0	0	150
Bachelor's	48	29	13	23	17	7	5	3	77	6	6	0	0	5	30	1	3	1	6	1	1	0	0	1	283
Master's	29	12	8	19	14	9	3	0	40	4	2	0	1	5	21	0	0	2	4	0	0	0	0	0	173
PhD	5	0	4	2	3	2	0	0	6	1	2	0	0	1	3	0	1	0	0	0	0	0	0	0	30
Higher education	81	43	31	42	32	14	12	2	84	10	6	2	0	11	31	0	0	2	7	0	0	0	0	1	411
Industry/Vocational training	35	19	13	21	15	8	6	1	50	5	3	3	1	5	14	0	3	1	2	1	1	0	0	1	208
Teachers	24	15	14	19	3	5	3	1	30	3	0	0	0	2	7	0	2	1	0	0	0	0	0	0	129
Citizen Science	0	0	0	0	1	0	1	0	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	3	10
Total:	255	151	108	152	98	52	31	7	484	58	33	12	3	38	149	2	17	14	25	2	4	0	0	6	

Fig. 5 Co-occurrence heatmap of the CM types and research context (NOTE: totals count for the CM types that may have multiple types associated with a single document)

6.5 Conceptual Structure

The conceptual structure analysis aims to identify and understand the organization and themes within a specific field of research or a collection of scholarly works (Aria and Cuccurullo 2017). The analysis includes authors' keywords, keyword co-occurrences, and a conceptual thematic map.

6.5.1 Author's most Frequent Keywords in the Dataset

We identified 2244 unique author keywords, with some keywords having identical meanings. There are 458 (20%) author keywords that are mentioned in at least 2 different articles; 88 (4%) keywords with 5 or more mentions across the publications; and 25 (0.1%) keywords with 9 or more references (more details are in Figure A.7). We combine different spellings of keywords and acronyms under a single keyword and employ a heatmap visualization to analyze the data. We mention the number of documents that have grown over the past 5 years (2018–2023). Generic terms such as modeling and conceptual modeling are at the top of the list. There is relative popularity and growth of topics related to software and UML modeling, BPMN and (business) process modeling, data modeling, and scientific modeling. In other words, in this dataset, keywords of the core CM are the most popular, which is likely a consequence of the delimitation of this study's search string.

6.5.2 Themes Based on Author's Keyword Co-Occurrence

To further explore the thematic structure of our collection, we conduct an author's keyword co-occurrence analysis. Clusters can be considered as research topics or themes. In this analysis, we use the Walktrap clustering algorithm by Pons and Latapy (2005) as one of the most prominent approaches to clustering, number of nodes 100, normalization by association, and removing isolated nodes (typical in bibliometric studies). We obtained 77 keywords (most frequently mentioned) and 11 clusters through the analysis (Table 3). We name the clusters based on our interpretation of the associated cluster keywords. The frequency of author keywords within each cluster is tallied to indicate the cluster's relative magnitude.

The author's keyword co-occurrence network clusters (Table 3). The network clusters are additionally visualized in the conceptual network structure in the Appendix (Figure A.1). Table 3 shows a detailed breakdown of the modeling type and the associated (learning) topics, concepts, and methods often co-occurring. The table represents the most prevalent approaches, as analyzed via the Walktrap clustering algorithm in a typical Bibliometrix analysis procedure (see description above). After finding the clusters, we added the frequency of all the keywords (including the modeling type and the associated topics), separated by a semi-colon. Thus, frequency represents the global keyword frequency within the clusters.

Based on the analysis of the clusters, we find several notable themes. Firstly, some clusters have more keywords and thus have a higher frequency (see clusters 1, 3, 4, 7). There are clusters with several modeling types (1, 3, 4) and others with a single modeling subtype (2, 11). Clusters with several modeling types could indicate the universal applicability of the learning topics, concepts, and methods across the CM subtypes, such as between data and conceptual (#1) or data, conceptual, software, and enterprise modeling (#4).

Several typical learning approaches can be discerned within each cluster, including prototyping, model-based reasoning and learning, problem-solving, e-learning, gamification, scaffolding, formative education, instruction design, project-based learning, and active learning. There are also typical research methods among certain modeling types: empirical study and prototyping occur in the data/conceptual modeling cluster, and experiments are typical in process modeling. There are also some related terms across the modeling types that embody the thought processes required for modeling. They should be systems-oriented, model-based, and computational, with argumentation and abstraction capabilities. Overall, Table 3 presents a broad-stroke picture of CM education.

6.5.3 Conceptual Thematic Map (Motor, Basic, Niche, and Emerging/Declining Themes)

Thematic mapping categorizes four types of themes based on centrality and density (Cobo et al. 2011). A theme with high centrality strongly connects with other themes, indicating an influential role. A high-density theme strongly concentrates on related elements or content, indicating high internal coherence. Thus, motor themes (high density and centrality) are mainstream themes in literature and relevant for developing and structuring the research field. Basic themes (low density and high centrality) are generic and typical for transversal research. Niche themes (high density and low centrality) are focused on a particular topic. Emerging or declining themes (low density and centrality) are weakly developed, on the decline, or are emerging themes to be further developed.

We performed a conceptual thematic map analysis (see Figure A.6 in the appendix) based on the authors' keywords using the Walktrap clustering algorithm with a minimum frequency of 5 keywords per cluster, a default recommendation by Bibliometrix designated to keep the broad and not too specific overview. We identify 9 themes via author keywords (Table 4) and interpret them according to the clusters' CM subtypes and learning topics. The frequency of keywords indicates the relative size of the cluster. Counting the frequency of keywords is the same as the one described in Sect. 4.5.2. The frequency indicates the most critical topics in the CM education within the obtained data sample.

There are two Motor themes: cluster 1 (Conceptual, software, IS, etc.), being the largest, and cluster 2 (Science and mental modeling), which approaches the niche type (likely due to the focus on mental modeling, a niche topic). There are also three basic (transversal) themes: process, data, ontology, engineering, simulation, computational, and agent-based modeling (clusters 7–9). Enterprise and conceptual modeling with modeling tool development and prototyping (cluster 4) and class and sequence diagram (cluster 3) are classified as niche types. These topics have low centrality and high density, meaning they have a solid continual research stream that is not well connected with broader themes. Finally, two emerging or declining themes

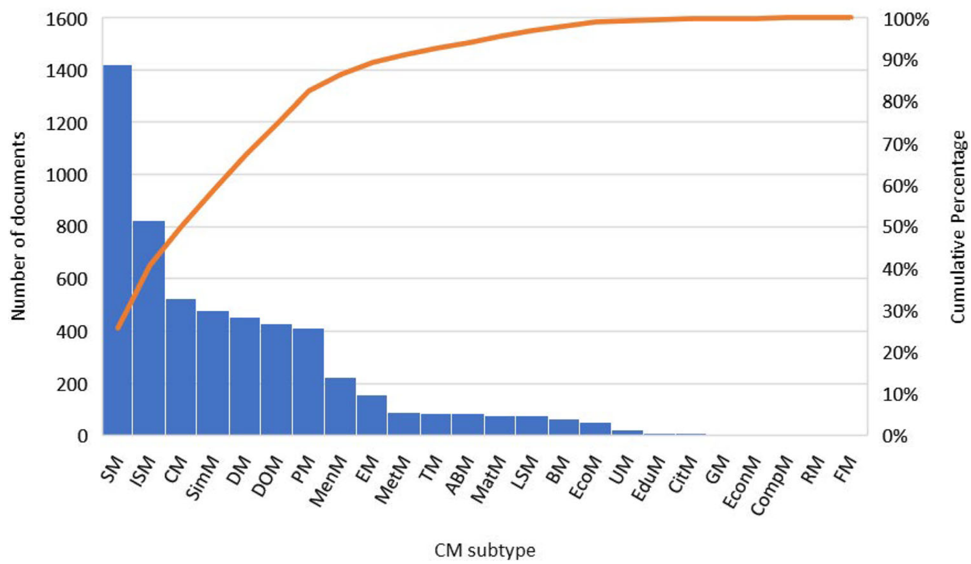

Fig. 6 Pareto chart of the number of authors (red line) publishing across CM subtypes

exist: science modeling with intelligent tutoring systems in physics education (cluster 5) and modeling-based learning (cluster 6). These topics can be considered ones that give a global field outline.

Our Core CM subtypes (belonging to cluster 1), along with science modeling (within cluster 2), are the most prevalent subtypes. We also observe that enterprise modeling is a niche. In contrast, business modeling (e.g., business model canvas) and other types, such as financial and economic modeling, are not represented due to their minimal presence in the sample and the algorithm's emphasis on significant underlying structures.

Learning topics across the clusters include the use of e-learning, formative assessment, feedback, and intelligent tutoring systems, instructional design, promoting computational thinking, model-based reasoning, studying conceptual change of the students, visualization techniques, active, experiential and project-based learning, model- and modeling-based learning and inquiry, gamification, modeling tool, and prototyping. Given our research objective, we argue that these candidate approaches can be applied across the CM subtypes. We elaborate further on learning topics in Sect. 4.8. The themes are like those mentioned in Table 3 above since both rely on the author's keywords.

6.6 Social Structure

Social structure analysis indicates how authors, institutions, and countries interact based on co-authorships of scientific documents (Aria and Cuccurullo 2017). Such collaborations often serve as the backbone of public knowledge (Taber 2013). Furthermore, the social structure is an essential reference for interpreting new knowledge.

6.6.1 Author's Scientific Production and Specialization versus Generalization in Research Interests

There are 2407 authors across 1064 documents. Lotka's Law (evaluation of the productivity of the authors) describes the frequency of publication by authors in each field. We observe 2037 authors (84.5%) who co-authored exactly 1 document in the sample; 227 authors who co-authored 2 documents (9.5%); 79 authors who co-authored 3 documents (3.3%) and 59 authors who co-authored 4 or more documents (2.5%). Hence, we consider authors with at least 4 publications in the sample as core authors.

According to Pareto's chart (Fig. 6), about 90% of the authors have published papers on science, information systems, simulation, data, domain and ontology, and process modeling. The remaining 10% of authors published in the remaining subtypes: Mental, Enterprise, Meta-, Technical, Agent-based, mathematical, learner's and students', business, and ecological modeling. Given the research scope, we observe a relatively lower number of authors publishing in Process, Enterprise, and Business modeling compared to excluded subtypes like Simulation modeling or subtypes with fewer terms in the search string, like Science Modeling. There are several possible reasons: (1) research interest across CM subtypes is imbalanced, (2) there are specific, more mature CM subtypes that have been in focus for a more extended time period (also with more authors, like Science Modeling), or (3) specific CM subtypes are addressed by fewer, but more productive authors (e.g., there are 2.65 documents per author in IS modeling and 2.8 documents in Science modeling on average).

We further analyze specialization versus generalization of research interests across authors. To achieve this, we determine the quantity of distinct CM subtypes that a particular author has contributed to (see Table A.5). About 67% of authors have published on one or two CM subtypes (specialized authors), 17% on three CM subtypes (borderline generalists), 10% on four or more CM subtypes (generalists), and 6% did not associate with any CM subtype. One author has contributed to a maximum of 11 CM subtypes, while another has published in up to 9 subtypes.

We also calculated the ratio of CM types per document per author: the number of documents is divided by the number of CM subtypes (where 1 is an absolute specialization on only one topic). On average, including outliers, there are 1.8 CM types per document for authors (like 1.83 CM subtypes per document). However, about 40% of the authors have a paper only in a single CM type, 70% in a paper in two CM subtypes, 80% in 3 CM subtypes, and 90% in 4 CM subtypes. Based on these findings, we claim that a great majority of the authors in the sample can be considered specialists.

6.6.2 Most Cited Authors

We find the 30 most influential authors (Fig. 7) as measured by the Hirscher (H-)index of local citations, or the number of citations among other documents within the analyzed 1064 dataset (often used for ranking authors in Bibliometrics), which is equal to 4 or higher. They represent the top 1.2% of 2406 authors in the sample.

The most cited authors (using only publications from the dataset) may vary slightly if using total global citations, that is, the number of all citations among all the publications within and without the 1064 dataset (Total Citations, or TC), or the number of published documents and tend to be generalists, who published in over three CM subtypes.

Except for 4 authors, every top author published an article associated with science modeling education, being the most popular topic. Second to that is conceptual and domain/ontology modeling. Third in popularity among these authors is IS, data, and simulation modeling. Fourth is process, enterprise, meta- and learner and student modeling. Finally, there are business, mental, ecological, and agent-based modeling.

6.6.3 Author's Collaboration Networks (Co-Author Groups)

To analyze the authors' collaborations, we used the Walktrap algorithm with a normalization through association, considering the 50 most popular authors.

We identify 15 clusters of co-authors (Fig. 8 and Figure A.2). A direct connection author network comprises 2, 3, or 5 authors who co-authored the same documents. An indirect-connection network is a group of co-authors connected via one co-author. Primarily, direct connection networks are smaller, usually having the size of 2–3 co-authors researching similar topics. The indirect connection networks have 4 to 5 co-authors and rely on several central authors (e.g., Snoeck M. and Krajcik J.). The number of citations and publications is usually higher. In the last column, we also calculate the average number of documents by the total number of CM subtypes (where 1 refers to the group writing papers only about one CM subtype). We see that most author groups are specialized and address, on average, about 1 to 2 CM subtypes, fewer explore 2 or 3 CM subtypes, and only 3 groups (#6, #7, #11) are generalists and explore 3 or more CM subtypes. However, compared to the average author (see Sect. 4.6.1), these groups publish in 3 CM subtypes at least once, pointing to the correlation between high research productivity and interest in multiple CM subtypes.

Table 5 Top countries based on the produced number of documents

#	Country	# docs	Avg. Articles Per Year (1982 to 2023)	Total Citations	Avg. Article Citation
1	USA	435	10.875	4635	20.33
2	GERMANY	125	3.125	1004	14.34
3	CHINA	59	1.475	307	9.3
4	JAPAN	57	1.425	60	3
5	NETHERLANDS	55	1.375	403	14.39
6	UK	51	1.275	372	14.88
7	AUSTRALIA	48	1.2	969	42.13
8	SPAIN	48	1.2	323	11.96
9	BRAZIL	44	1.1	372	16.17
10	BELGIUM	38	0.95	292	10.43

#	Name	H-index (LC)	Current or latest known institution affiliation	TC	Articles	ISM	DOM	DM	CM	SM	PM	EM	MenM	LSM	MetM	MatM	BM	SimM	TM	UM	RM	CompM	EcoM	GM	EduM	EconM	FM	ABM	CitM	Total
1	*SCHWARZ C*	11	Michigan State University	1206	13	0	2	0	2	13	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	21
2	*SNOECK M*	10	KU Leuven	221	24	11	13	6	23	6	1	5	0	2	1	1	0	5	0	0	0	0	0	0	0	0	0	0	0	74
3	*ZANGORI L*	8	University of Missouri	204	11	0	3	0	3	11	0	0	2	1	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	23
4	*SEDRAKYAN G*	8	University of Twente	156	11	6	4	0	11	2	0	1	0	0	1	1	0	5	0	0	0	0	0	0	0	0	0	0	0	31
5	*MITROVIC A*	6	University of Canterbury	443	7	1	4	3	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12
6	*WU H*	6	University of Taiwan	181	8	0	1	0	1	7	0	0	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	13
7	*CONSTANTINOU C*	6	University of Cyprus	160	9	1	1	0	1	9	0	2	1	1	0	0	0	3	0	0	0	0	1	0	0	0	0	0	0	20
8	*FORBES C*	6	University of Texas	151	8	0	3	0	3	8	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	17
9	*KRAJCIK J*	5	Michigan State University	1139	9	2	0	0	0	9	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	14
10	*DAVIS E*	5	University of Michigan	778	5	0	0	0	0	5	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
11	*ZACHARIA Z*	5	University of Cyprus	251	8	1	0	0	1	8	0	0	1	1	0	0	0	3	0	0	0	0	1	0	0	0	0	0	0	16
12	*JUSTI R*	5	Universidade Federal de Minas Gera	224	10	0	1	0	0	10	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	13
13	*BISWAS G*	5	Vanderbilt University	148	6	0	4	0	2	6	1	0	0	2	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	20
14	*CAMPBELL T*	5	University of Connecticut	90	5	0	0	0	0	5	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	8
15	*OH P*	5	Gyeongin National University of Edu	89	5	0	0	0	0	5	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	8
16	*KRUGER D*	5	Freie Universität Berlin	70	5	0	0	0	0	5	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8
17	*LETHBRIDGE T*	5	University of Ottawa	56	5	5	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
18	*STRECKER S*	5	University of Hagen	39	9	1	0	5	8	4	1	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	22
19	*JAN VAN DRIEL*	4	University of Melbourne	290	5	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
20	*LOUCA L*	4	European University-Cyprus	231	7	1	0	0	0	7	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
21	*CHINN C*	4	Rutgers University	147	4	0	1	0	1	4	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
22	*LEWANDOWSKI H*	4	University of Colorado Boulder	141	7	0	0	0	0	7	0	0	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	11
23	*VAN J W*	4	University of Utrecht	66	5	0	4	0	2	4	0	0	1	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	15
24	*CLAES J*	4	Artevelde University of Applied Sce	56	4	0	1	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
25	*VANDERFEESTEN I*	4	KU Leuven	56	4	0	1	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
26	*WEBER B*	4	University of St. Gallen	55	6	1	1	1	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
27	*HWANG F*	4	National Taiwan Normal University	54	4	0	1	0	1	4	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	8
28	*BOGDANOVA D*	4	KU Leuven	47	9	4	7	5	9	2	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31
29	*ROSENTHAL K*	4	University of Hagen	35	8	1	0	4	6	3	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16
30	*TERNES B*	4	University of Hagen	27	7	1	0	2	7	1	1	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	15
					Total:	36	52	26	81	151	19	17	18	14	10	3	3	31	2	0	0	0	6	0	0	0	0	2	0	

Fig. 7 Most cited authors

#	Authors	Network connecti on type	# authors	CM subtype	LC	TC	# docs.	ISM	DOM	DM	CM	SM	PM	EM	MenM	LSM	MetM	MatM	BM	SimM	TM	UM	RM	CompM	EcoM	GM	EduM	EconM	FM	ABM	CitM	Total	Doc./Tot
1	KRAJCIK J;WU H;DAVIS E;BIELIK T;CHANG H	Indirect	5	SM	9	2155	30	2	1	0	1	29	1	0	4	0	3	1	0	4	2	0	0	0	0	0	0	0	0	1	0	49	1,6
2	BIDER I;HENKEL M	Pair	2	EM	0	27	11	0	2	0	2	2	1	10	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	25	2,3
3	JUSTI R;GILBERT J;VAN D J	Indirect	3	SM	8	651	20	0	2	0	0	20	0	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	26	1,3
4	CAMPBELL T;OH P	Pair	2	SM	19	179	10	0	0	0	0	10	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0	2	0	16	1,6
5	DORI D;DORI Y	Pair	2	CM	0	60	8	2	0	0	8	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	1,5
6	BUCHMANN R;GHIRAN A	Pair	2	"Core" CM, MatM and	0	13	9	6	9	0	9	4	4	4	0	0	5	0	2	0	0	0	0	0	0	0	0	0	0	0	0	43	4,8
7	SNOECK M;SEDRAKYAN G;BOGDANOVA D;DE W J	Indirect	4	"Core" CM, SM and	54	480	48	21	27	11	47	11	1	11	0	3	2	3	0	10	0	0	0	0	0	0	0	0	0	0	0	147	3,1
8	DEMUTH B;LETHBRIDGE T;MUSSBACHER G	Indirect	3	ISM and DOM	4	99	15	15	5	3	1	1	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	1,9
9	CONSTANTINOU C;ZACHARIA Z;LOUCA L	Direct	3	SM and SimM	0	642	24	3	1	0	2	24	0	2	3	2	0	0	0	6	0	0	0	0	2	0	0	0	0	0	0	45	1,9
10	CHINN C;DUNCAN R	Pair	2	SM	6	291	8	0	2	0	2	8	0	0	3	2	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	20	2,5
11	VAN J W;BOLLEN L	Pair	2	DOM and SM	1	121	9	0	6	0	3	8	0	0	1	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	25	2,8
12	KRELL M;KRUGER D	Pair	2	SM and MetM	16	106	10	1	0	0	0	10	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	1,7
13	SCHWARZ C;ZANGORI L;FORBES C	Direct	3	DOM, CM and SM	86	1561	32	0	8	0	8	32	0	1	4	2	1	0	0	1	0	0	0	0	4	0	0	0	0	0	0	61	1,9
14	STRECKER S;ROSENTHAL K;TERNES B	Direct	3	DM, CM and SM	0	101	24	3	0	11	21	8	2	3	0	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	53	2,2
15	WEBER B;CLAES J	Pair	2	PM	7	111	10	1	2	1	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	1,4
							Total:	54	65	26	104	169	19	33	15	12	23	4	6	39	2	0	0	0	6	0	0	0	0	4	0		

Fig. 8 Authors' collaboration network heatmap (based on co-citation)

6.6.4 Countrie's Scientific Production

Based on the author's affiliation with a country at the time of document publication, Table 5 presents the 10 most frequent countries (also see Figure A.3 for a global map visualization). They account for approximately 66% of the total documents. These countries are considered developed economically (with the potential exception of Brazil and China), in line with the brain drain phenomenon (Vega-Muñoz et al. 2021). Pedagogical researchers may use convenience sampling by using students as the closest available subjects, and the cultural context differs across different countries for students, impacting the validity and reliability of transferring findings. For instance, most psychological studies are based on US students, ignoring 95% of other populations (Arnett 2008). We assume that the situation is comparable in our context, where most CM education research is based on evidence from developed countries.

6.7 Intellectual Structure

The intellectual structure shows how an author's work influences the scientific community (Aria and Cuccurullo 2017). We analyze the most cited articles and outlets and perform bibliographic coupling.

6.7.1 Most Cited Articles

The top 20 papers (about 2%) were globally cited over 100 times (see Table A.6). There is a difference between top papers ranked by global and local citations (see Tables A.6 and A.7). Local citations are the number of citations within the dataset (1064); global citations relate to the global interest (all citations). We observe that most globally cited papers are situated in the Science Modeling subtype, suggesting that Science Modeling education is more popular, broader, or further integrated into the CM education field than, for instance, the core CM subtypes. We see more papers about core CM education when considering the most popular locally cited papers.

6.7.2 Publishing Outlets

We identified 601 unique publication outlets (see Figure A.4 for the top 32 sources based on the # of published articles). Bradford's law states that if a number of articles sort outlets into three groups, each with about one-third of all articles, then the number of journals in each group would be proportional to 1:n:n^2. Consequently, the core zone has 5.6% of outlets (34 outlets) containing 351 documents; the middle zone has 36.2% (220 journals) with 358 documents; and the minor zone 58.1% (347 outlets) containing 355 documents.

We analyze the top 32 outlets (based on the filter of 5 or more publications). The science Modeling subtype has more dedicated journals to the Science Education field and specific subtopics (like Chemistry or Physics education journals). Science Modeling constitutes a considerable part of Science Education (e.g., given model-based science learning; Taber 2013). We observe a lack of a similar trend in IT or Business education – we do not find "model-based learning" in IT or business education. Also, there are no dedicated IT or business education journals except for the Journal of Information Systems Education. Incredibly, there are no journals devoted to core CM education or core CM subtypes education (e.g., on business modeling education). Hence, we suggest that there is an apparent lack of dedicated venues to publish CM education research, impeding knowledge production and dissemination.

6.7.3 Bibliographic Coupling (Emerging Research Topics)

The intellectual structure of the field can be explored by using a bibliographic coupling – two related documents using the same reference, with the "coupling strength" being more substantial the more two given documents refer to the same documents (Kessler 1963).

Thematic clusters are established based on the citing publications, with recent and niche publications gaining visibility through bibliographic coupling. Hence, this approach provides a representation of the *present* of the research field (Donthu et al. 2021). Bibliographic coupling in Bibliometrix shows two measures: impact and (betweenness) centrality. Betweenness *centrality* is considered an indicator of the interdisciplinarity of documents. However, only after normalization and in local citation environments – otherwise, the influence of degree centrality (size) overshadows the betweenness-centrality measure (Leydesdorff 2007).

In Bibliometrix, we use the following settings: coupling measured by references, impact measure based on local citation score, cluster labeling by authors' keywords, number of coupling units (documents) equal to 300, clustering algorithm Walktrap, minimum cluster frequency of

Table 6 Bibliographic coupling themes

#	CM subtypes	Learning topics	Freq	Centrality	Impact
1	(Business) process, conceptual, domain, BPMN, UML modelling, process mining	Automated feedback, software engineering and CS education, empirical study	47	0.30	2.99
2	Scientific, computational modelling	Science education, scientific practices, inquiry-based learning and reasoning, model-based inquiry, modeling instruction, scaffolding, abstraction, affordance	51	0.35	2.89
3	Conceptual, data, database modelling, agile modelling method engineering	Cognitive breakdown, mixed methods, bloom's taxonomy, cooperative learning, feedback automation, instructional design	10	0.31	1.00
4	Conceptual, database, ER, BPMN, class modelling	Empirical, artifact-creation process, automatic formative assessment and feedback, between-subject design, chunks	21	0.25	1.00
5	Data, enterprise, behavioral simulation, BPMN, (business) process, computational modelling	Cognitive apprenticeship, collaboration, community identification, competence profile, conceptual understanding, degree programme	22	0.18	1.18
6	Scientific modelling	Science education, water, elementary science, model-based learning, modeling-based learning, modeling competence, argumentation, block-based coding	147	0.38	2.45

Table 7 Summary of research opportunities on Conceptual Modelling education

#	Research avenue	Sub-avenue	Research opportunities
1	Toward a unified theoretical foundation of CM	Development of a Unifying Theory of Conceptual Modeling (CM)	Researching the foundational questions and principles that underpin CM across various domains
		Cross-Disciplinary Integration	Exploring how CM can be recognized and utilized as a transdisciplinary independent field that integrates various scientific and engineering domains
		Comprehensive Taxonomy of CM Subtypes	Developing a detailed taxonomy of CM subtypes and associated modeling languages, distinguishing CM from generic and technical modeling practices
		Common Terminology and Conceptual Understanding	Developing common grounds in terminology and conceptual understanding across CM subtypes to enhance communication and collaboration
		CM education as a standalone discipline	Positioning CM education as a standalone discipline as mathematics education, on the merits of CM being a transdiscipline equal to mathematics
		Dedicated Outlets for CM	Creating specialized venues and journals for CM and CM education to facilitate focused research and dissemination
2	CM subtypes in CM education research	Exploration of Underexplored CM Subtypes	Investigating education in less-studied CM subtypes: enterprise, business, user, mental, meta-, citizen and ecological modeling
		Interweaving Popular and Less Popular Subtypes for Comprehensive Curricula Development	Studying the interrelationships and integration of widely studied CM subtypes (e.g., data, IS, conceptual modeling) with less popular CM subtypes, in particular to move towards a comprehensive interdisciplinary CM education curricula
		Synergy Between Core and Non-Core CM Subtypes	Examining the potential for integrating non-core CM (e.g., simulation and agent-based modeling) with core CM subtypes in the educational approaches
		Standardized vs. Domain-specificity in Modelling Languages	Researching the benefits and challenges of using standardized and domain-specific modeling languages in CM education and across various CM subtypes
		Business-Oriented CM Education	Addressing the research gap in business-oriented CM education and developing systematic approaches to enhance expertise in this area
3	Applying and transferring learning approaches across CM subtypes	Transferring Successful Learning Theories and Approaches	Exploring the integration and application of various learning approaches shown effective across different CM subtypes as well as outside the CM education field (like Zone of Proximal Development, Bloom's Taxonomy)
		Emerging Learning Theories	Researching the application of emerging learning theories (e.g., ubiquitous and mobile learning) in CM education
		Connectivist Learning Paradigm	Researching CM education from the perspective of the Connectivist Learning Paradigm
		Gamified and Game-Based Learning	Investigating the potential and effectiveness of gamified and game-based learning in CM education
		Adaptation of Cognitive Frameworks	Applying cognitive frameworks from science modeling education to broader CM education to improve conceptual understanding and adaptability among students
		Model-Based Thinking and Inquiry	Applying model-based thinking and inquiry learning approaches from science modeling to business and IT education to unify learning approaches
		Learning Objectives in CM	Defining learning objectives in CM to move toward a systematic and unified education
		Applied vs. Theoretical Learning	Examining the balance between applied-oriented methods of learning and theoretical learning and its impact on the learning outcomes and the development of CM as both practical and theoretical discipline

Table 7 continued

#	Research avenue	Sub-avenue	Research opportunities
4	Extending and transferring research methods in CM education	Development of Theories and Literature Reviews	Conducting theory-building research and comprehensive literature reviews to establish a stronger theoretical foundation for CM education, likely using science modeling education as a guideline for the CM education field as a whole
		Longitudinal Studies	Implementing longitudinal research to verify the long-term impact of CM teaching methods and curricula
		Quantitative Experimentation	Introducing more quantitative experimentation to balance qualitative methods and to confirm the learning effects of specific interventions
		Physiological Data Collection Methods	Employing physiological methods (e.g., fMRI, EEG, eye-tracking) to gain insights into cognitive processes during modeling tasks
5	The context in CM education research	Diversification of Research Across Educational Levels	Expanding CM studies across broader educational levels: primary, secondary, vocational, and PhD education
		Integration with Industry and Vocational Training	Researching the application of CM education in industry and vocational training contexts to bridge the gap between academic and practical contexts
		Citizen Science	Investigating innovative ways to integrate citizen science and modelling with CM education to engage the public in scientific inquiry and promote CM skills in the public
		Country and Cultural Contexts	Studying the impact of country and cultural contexts on CM education to improve external transferability of results and to develop more globally applicable teaching strategies
6	Generalism and specialism in CM education and with researchers	–	Exploring the effects of specialization and generalization of CM researchers and students, and its impact on academic careers, research output, and student learning in CM education
7	Practical implications for CM educators	Balanced Curriculum Design	Maintaining the optimal balance between broad, generalist, theoretical and specific, focused, applied instruction in CM education
		Comprehensive Educational Programs	Developing comprehensive educational programs that span multiple degrees and educational levels to provide a deep and broad understanding of CM
		Adoption of New Learning Paradigms	Adopting learning paradigms from other CM subtypes to enhance CM education
		Conscious Adoption of Learning Paradigm Stance	Adopting learning paradigms, theories and approaches more consciously and systematically

5. The procedure of counting the frequency of keywords is the same as the one described in Sect. 4.5.2. (Table 3).

We identify 6 clusters in Table 6 (also see Figure A.5): (I) automated feedback in Process and IS modeling via empirical studies; (ii) model-based inquiry and scaffolding in Science and Simulation Modeling; (iii) instructional design of the cooperative learning and feedback automation via mixed methods in CM and Data Modeling; (iv) automatic formative assessment and feedback and learning chunking in CM, Data, Process, and IS modeling via empirical research; (v) cognitive apprenticeship, collaboration, competence profile and conceptual understanding in Data, Enterprise, Process and Simulation modeling; (vi) model-based learning and modeling competence in elementary science in Science Modeling.

Based on keyword frequency, clusters 1, 2, and 6 emerge as the most critical. These clusters primarily feature scientific modeling as the subtype with the greatest emphasis, followed by some core CM subtypes, including process, UML, data, conceptual, and domain modeling. While the core subtypes receive greater emphasis in Tables 3 and 4, the findings of Table 6 are comparable to those results. We also find that enterprise modeling carries limited significance, and specific CM subtypes, such as economic and financial modeling, are not represented at all. The results also contain additional learning topics that did not appear in the previous analysis, such as argumentation, cooperative learning, cognitive apprenticeship, and competence profile.

6.8 Automatic Content Analysis: Learning Theories

Finally, after performing bibliometrics, we conducted an automatic content analysis in NVivo, in which we coded the frequency of learning paradigms, theories, and approaches per CM subtype (Fig. 9).

Learning theories are applied with varying frequency: some are frequently applied, others are used less often, and some are specific to certain types of modeling. We have identified several major categories that include sub-theories: behaviorism, cognitivism, constructivism, connectivism, and humanism. Additionally, we include extra categories of learning theories that do not clearly fit into any recognized category in the literature.

Constructivist learning is the predominant paradigm in CM education, followed by the cognitivist paradigm (including cognitive load theory, multimedia learning theory, social cognition theory, and the widespread cognitive development theory). In some papers, CM is viewed from a constructivist perspective wherein models help to construct and frame knowledge (e.g., Taber 2013). We observe studies arguing and viewing models (e.g., mental modeling) from a purely cognitivist perspective, focussing on helping students to advance their thinking processes (e.g., George and Domire 2017). Further references take an intermediate position and touch upon both constructivism and cognitivism, such as Brewe and Sawtelle (2018), who advocate constructivism but refer to Rogoff (1990), who discusses Vygotsky's and Piaget's ideas on cognitive development theory through social interaction.

Behaviorism, focusing on using external stimuli and reinforcement in learning, has been mentioned a few times in the sample, even though some authors cherish the move away from behaviorism (Taber 2013). Connectivism is a paradigm that uses a constructivist approach while acknowledging that knowledge is distributed socially, and learning is mediated via technology. Given that CM is often performed in modeling tools and can be done in collaboration, it is remarkable that it is not used in our sample. Humanism places a higher focus on the moral development of students (Huang et al. 2019). It refers to a more generic and abstract CM, which may have greater connections with philosophy education but is another under-researched learning approach in CM education literature.

Frequently used learning theories, approaches, and techniques, often, but not consistently, across several CM subtypes, include Learning objectives (82), constructivism (32), active (67), experiential (31), game-based (22), problem-based (29), project-based (37), self-regulated (39), blended (21) learning theories. Also, E-learning (91), scaffolding (127), formative assessment (29), gamification (33), model-based inquiry (55), and model-based reasoning (65). These theories are often also mentioned in Tables 3, 4, and 6, where they were used as keywords to define the conceptual structure.

Some theories are mainly used in specific CM subtypes and little or not at all in others. For instance, scaffolding, learning objectives, model-based inquiry, and model-based reasoning are extensively used in science modeling but significantly less so in core CM. Active learning is often used in science, IS process, and conceptual modeling but not in other types of modeling.

We included all the theories to test their prevalence in the data sample. Figure 9 includes 20 learning theories not referenced in any of the 1064 papers (e.g., programmed instruction, social learning theory, cognitive dissonance theory, conditions of learning, elaboration theory). Some of these theories can be considered very fundamental and prevalent elsewhere, such as the zone of proximal development, which is as popular as Bloom's taxonomy and is one used for scaffolding and formative assessment (Margolis 2020), which are popular approaches in CM education (Fig. 9). This can evidence a lack of deep understanding of the pedagogical theories (Rosenthal et al. 2019). Some learning theories, like ubiquitous learning (u-learning) or mobile learning (m-learning), have not yet made their way into the domain of CM despite being described as major shifts in learning paradigms (Cope and Kalantzis 2017).

Remarkable is the case of "collaborative learning." Although there were some papers (10) that had "collaborative learning" as an author keyword, its frequency in our analysis is 0 (see Fig. 9). The reason lies in applying a cutoff value (as explained in Sect. 3.5), where a minimum of three mentions is required to ensure a 90% certainty for a keyword to be relevant. This can hint at unsystematic or only sporadic usage of terms pertaining to learning theories (Rosenthal et al. 2019).

7 Discussion of Results and Future Research Avenues

This section discusses the results of the presented analysis and describes future research avenues, as typical for literature reviews (Rowe 2014). Compared with the initially explained research gaps of a lack of cross-disciplinary research in CM (**RG1**) and a lack of unified and systematic CM education (**RG2**), we provide an analysis to contribute towards the latter. However, regarding the first research gap (**RG1**), the present work also aims to systematize CM and CM subtypes for inclusion and exclusion criteria of the conducted literature retrieval and recognize the need for a discussion on CM and CM education as standalone disciplines (see Sect. 5.1). Concerning the second research gap (**RG2**), we provide a discussion of results and propose

	Learning theory category/name	ISM	DM	DOM	CM	PM	EM	BM	UM	SM	MenM	MetM	EcoM	EduM	MatM	SimM	Comp	ABM	LSM	TM	RM	GM	EconM	FM	CitM	Total
Behaviourism	Behaviourism	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	Direct Instruction	2	1	0	0	0	1	0	0	2	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	9
	Learning Objectives	12	3	4	9	5	4	3	1	21	3	5	0	0	1	8	0	0	1	0	0	1	1	0	0	82
	Programmed Instruction	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Social Learning Theory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cognitivism	Cognitivism	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	Attribution theory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Cognitive Development	2	1	0	1	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	7
	Cognitive dissonance theory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Cognitive load theory	1	2	1	2	4	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	12
	Conditions of learning	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Elaboration theory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Multimedia learning	3	2	3	3	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	15
	Social cognitive theory	1	2	2	1	0	1	0	0	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	12
Constructivism	Constructivism	6	3	1	4	1	0	1	0	9	0	1	0	0	0	4	0	1	0	0	0	0	0	0	1	32
	4C-ID	2	0	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
	Active learning	11	4	3	7	5	2	2	0	18	2	3	0	0	2	6	0	1	0	1	0	0	0	0	0	67
	Case-based learning	1	0	0	1	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
	Example-based learning	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	Game-based learning	3	2	3	3	2	1	1	0	2	0	1	0	0	1	2	0	1	0	0	0	0	0	0	0	22
	Problem-based learning	3	2	2	3	2	0	0	0	9	2	1	0	0	0	3	0	1	1	0	0	0	0	0	0	29
	Project-based learning	7	2	2	7	2	0	1	0	10	1	1	0	0	1	2	0	0	1	0	0	0	0	0	0	37
	Activity theory	2	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
	Actor-network	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	Cognitive apprenticeship	4	3	0	0	1	0	0	0	2	1	0	1	0	1	2	0	0	0	0	1	0	0	0	0	16
	Collaborative learning	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Cooperative learning	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	Discovery-based learning	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	3
	Inquiry-based learning	1	0	1	1	0	0	0	0	6	0	0	0	0	2	2	0	1	0	1	0	0	0	0	0	15
	Self-regulated learning	5	3	4	6	0	1	0	0	9	0	1	0	0	2	5	0	1	1	1	0	0	0	0	0	39
	Situated learning	2	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	6
	Social development	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	Socio-cultural theory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Student learning theory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Connectivism	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hum.	Humanism	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Experiential learning	5	3	0	3	3	2	2	0	8	0	1	0	0	0	3	0	1	0	0	0	0	0	0	0	31
Additional theories	Blended Learning	1	2	3	3	2	1	0	0	6	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	21
	E-learning	16	16	10	14	7	3	1	0	15	2	2	0	0	2	2	0	1	0	0	0	0	0	0	0	91
	M-learning	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	u-learning	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Bloom's Taxonomy	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	Conceptual Change Theory	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	Dick and Carey Model	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Distributed Cognition	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	Flipped –classroom	0	0	0	1	0	1	1	0	3	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	8
	Instructional Design	1	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	Instructional Methods	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Concept attainment	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Delayed Feedback	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	Interleaving	2	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	Rapid Feedback	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Retrieval Practice	1	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	5
	Scaffolding	12	10	11	11	0	3	0	0	45	11	2	1	0	2	14	0	1	2	1	0	1	0	0	0	127
	Spaced Repetition	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Observational Learning	2	3	0	0	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
	Peer instruction	2	1	0	1	0	1	0	0	2	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	9
	Research programme trends	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Formative Assessment	4	5	0	2	3	2	0	0	7	1	1	0	0	1	3	0	0	0	0	0	0	0	0	0	29
	Gamification	5	6	3	3	3	2	2	0	4	0	1	0	0	1	1	0	0	0	2	0	0	0	0	0	33
	Learner-controlled learning	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Model-based inquiry	1	2	2	2	2	1	0	0	32	3	1	0	0	0	6	0	1	2	0	0	0	0	0	0	55
	Model-based reasoning	1	0	2	7	1	0	0	0	32	12	1	1	0	0	2	0	0	3	3	0	0	0	0	0	65
	Social Cognitive Theory of Self-Regulation	1	2	2	1	0	1	0	0	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	12
	Zone Of Proximal Development	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total:	75	37	30	57	28	14	10	1	109	9	19	1	0	11	41	0	8	5	4	1	1	1	0	1	

◀**Fig. 9** Frequency of learning paradigms, theories, and approaches (The "Totals" on the bottom and right count for the CM subtypes that may have multiple types associated with a single document)

future research avenues on the topics of CM subtypes in CM education (see Sect. 5.2), learning approaches (see Sect. 5.3), research methods (see Sect. 5.4), contexts in CM education (see Sect. 5.5) and insights regarding the social structure of CM education research (see Sect. 5.6). Overall, we argue for focused investigations into the education of specific CM subtypes and abstracting from subtype specifics to improve theoretical and practical understanding of the CM education field (e.g., via transferring the successful pedagogical approaches across the CM subtypes). We also explain the practical implications for teachers and educators in either CM subtype (see Sect. 5.7). Table 7 summarizes the research opportunities in the proposed future avenues and sub-avenues.

7.1 Toward a Unified Theoretical Foundation of Conceptual Modeling

The present inquiry has preliminary examined the theoretical boundaries within Conceptual Modeling (CM) theory via frequency analysis (Fig. 9). It is remarkable that in the dataset of 1064 papers classified broadly belonging to the CM education field, only 51 papers used 'conceptual modeling' as a keyword. This suggests that this term is not yet seen as an independent research topic. It thus prompts further research into the unified and standalone CM education discipline discussion (see Sects. 5.1 and 5.2) to make CM universally recognized. This speaks about a lack of a *generally accepted* unifying theory. Some theories (Thalheim 2010; Cabot and Vallecillo 2022) seek to advance such a unified theoretical foundation, yet it is not widely accepted. To advance CM education, it is imperative to define and comprehend the foundational questions underpinning CM rigorously.

We argue that CM must adhere to a vision that transcends current domain and function specificity limitations to become a genuinely transdisciplinary independent field. CM must integrate and serve various scientific and engineering domains. CM must also assume that modeling techniques are about the representation and manipulation of complex systems through abstraction (Cabot and Vallecillo 2022). Future conceptual modelers and educators of CM (in either of the subtypes) could recognize similarities and a solid conceptual foundation that extends their domain. We have paved the way by considering typically "core" CM subtypes (such as data or enterprise modeling) while trying to connect with broader modeling types, which may rely on the same principles (such as science modeling in physics and chemistry), in a path proposed by Ghiran et al. (2020), stating that modeling should be perceived inter-disciplinarily.

Moreover, developing a comprehensive taxonomy of CM subtypes and associated modeling languages is strongly advised. This includes a delineation of CM, and its distinctive attributes compared to generic modeling practices (Zarwin et al. 2014) or mathematical and technical modeling. During our research, establishing these distinctions posed considerable challenges and thus significantly impacted on the replicability of the research.

Our analysis shows that Science Modeling (as a CM subtype) has many dedicated publishing outlets. Because of an evident lack of dedicated publishing venues and outlets that cover core CM subtypes, we suggest creating overarching venues and outlets for research on CM and education in CM. This can stimulate CM educators to publish in tangentially related and not dedicated journals, promoting knowledge acquisition and dissemination. Conceptual modelers can then position themselves on the merits of being experts in a complex subject with a history that extends beyond 2000–4000 years old (Zarwin et al. 2014).

Related to this, core CM education publications lack integration with broader fields, unlike in science modeling (given much higher global citations of Science Modeling papers). Science modeling education has a more robust tradition of being related to model-based learning and science education, and we see that this is not the case for the core CM (with a few exceptions for IS modeling and CS education journals). However, we see potential in establishing these links (e.g., via dedicated literature reviews in the core CM education field).

CM education should provide a generalist background in multiple types of modeling in different CM subtypes to address the idea of CM as a standalone discipline. A common principle is that conceptual modeling is not an exact science but rather more artisanal, requiring creativity, intuition, and experience, making it like the natural modeling concept (Zarwin et al. 2014). This means that IT education could provide some generic approaches to systems modeling.

Researchers should be concerned with positioning CM education on the same level as mathematical and science education, on the merits of being a transdiscipline equal in importance and application (Cabot and Vallecillo 2022). This implies dedicated courses and universal acceptance across the disciplines. It is essential, at least at the higher education level, where business and IT professionals often unknowingly use (conceptual) models and thus lack the necessary conceptual and procedural knowledge (conscious) of what modeling is and how to do it.

7.2 Conceptual Modeling Subtypes in CM Education Research

Our investigation into the prevalence and co-occurrence of CM subtypes (see Fig. 3) across a significant corpus of academic literature has illuminated several patterns and gaps that warrant further exploration. There is an excellent variety of discussed concepts (2244 unique author keywords), but only 5% of these keywords (100) are repeatedly mentioned in 5 or more publications. This may indicate a divergence in research interests. This observation also indicates a lack of established common grounds in terminology and conceptual understanding of similar and related phenomena across the CM subtype education researchers (given the general prevalence of specialists in the CM education field), a gap the present paper aims to address.

The most frequently studied subtypes are scientific modeling (appearing in 486 papers), IS (300), data (189), conceptual (188), simulation (164), domain and ontological (151), and process modeling (127) (see Fig. 3). Subtypes with less academic coverage, each featuring fewer than 100 papers, include enterprise (58), business (25), user (9), mental (82), meta- (34), and ecological modeling (15). This distribution signals an overrepresentation of certain topics for a reason that is not entirely clear and can constitute a new research question. Future research should consider the subject's popularity and may consider interweaving with other subjects.

The dominance of science modeling and the integration of traditionally technical subtypes like IS and data modeling suggest a maturing field where cross-disciplinary applications are typical. However, the relative scarcity of literature on enterprise, business, user, mental, meta-, citizen, and ecological modeling points to areas ripe for scholarly attention.

There are 20 topics (clusters) from the core of CM and science modeling, different in size and impact on the CM education field (Sects. 4.6.2 and 4.6.3 in Tables 3, 4, and 6). Our findings resemble those of Rosenthal et al. (2019), who found that gamification, modeling tools, formative feedback and assessment, e-learning, learning management systems, and simulation are the prevalent themes in CM education. Beyond these themes, we also found additional themes like visualization, model-based inquiry/reasoning, and instructional design. Moreover, we explored how theories are distributed among the various CM subtypes (cf. Section 5.3). The conceptual structure analysis shows significant interconnectedness between CM subtypes (cf. Section 4.5). As such, it is not easy to make a strict separation between the topics/clusters, and often, a single CM subtype must be explained in relation to other CM subtypes.

Data, IS, conceptual, domain and ontology modeling are the most studied subtypes and are mostly interrelated in the sample analyzed. These types of modeling are closely related to each other in terms of the underlying phenomena and learning approaches. For instance, process modeling would be more business- and sequence-/flow-oriented, whereas these types of modeling are ontology- and IT-driven and are more static and structural. Process modeling could likely be better taught via dynamic simulation and visualization, showcasing its sequential nature, whereas other approaches could be suitable for ontology-based CM subtypes.

Business-oriented CM subtypes (including process, business, and enterprise modeling) are not popular topics in CM education research, though they are well-integrated with other core CM subtypes. Only process modeling (127 publications) is being explored considerably. This constitutes a major research gap of "business-oriented core CM" lacking in systematic approaches, contributing to the shortage of expertise in the workplace, as discussed in the introduction. The topics included analyzing the study of BPMN, process models, and how to perform automated feedback, experimentation, and gamification (see Tables 3, 4, 6). We suggest that the IT background of CM (e.g., associated with software engineering and computer science) is grounded in the business-oriented CM subtype education. IT systems are critical components of today's businesses, but they should not be the core focus of general business students. As such, future research in CM education should consider exploring topics that are more distinct from IT business-oriented modeling (like business model canvas). Students' educational background may impact CM (Figl 2017); thus, CM education may need significant adaptations based on the type of CM.

Certain modeling languages are preferred when teaching CM subtypes. In process modeling, it is BPMN; in IS modeling, in conceptual and data modeling, UML and ERD seem dominant (see Table 3). As such, these are some commonly used languages in teaching CM. Using these languages as a defacto standard and using them across more CM subtypes would facilitate the transfer of educational approaches, thus contributing towards the unification of CM. Future research should nevertheless consider the issue of agility in modeling languages and DSML (domain-specific modeling languages). It could be of value to use standardized languages in teaching, but it should remind students to be able to adapt when needed (Karagiannis et al. 2020).

Science modeling is the most frequently studied subject and is closely associated with the technical aspects of mathematical, simulation, and data modeling. Various topics were researched in this subtype: water studies, chemistry, physics, biology, and ecology. Science modeling has often co-occurred with conceptual modeling, suggesting major underlying principles between both. We identify six present and recently emerging research topics in core CM and science modeling (see Table 6). The focus is on automatic (formative) assessment, cooperative learning, cognitive apprenticeship, scaffolding, and promoting modeling competence and argumentation with models using empirical and mixed methods. As such, the approaches are rather holistic and focus on training mental facilities (see the high co-occurrence between science and mental modeling in Fig. 3). This may represent a unique aspect of scientific modeling, which, despite its foundation in precision and empiricism, centers on universal and transferable skills. We argue that this characteristic is crystallized in the model-based reasoning/learning approach in science modeling and should be considered in other fields, such as business/IT modeling education.

Mental and meta-modeling are specific types of CM, often considered tangentially related to CM (Buchmann et al. 2019; Taber 2013). Both are rather fundamental subjects, explaining the structure and behavior of conceptual models. So, they could be helpful in studying the fundamental rules of CM in any given discipline. It was a relatively rarely studied topic (just 82 and 34 studies, respectively). Mental modeling often co-occurs with Science Modeling as a subtype and meta-modeling with core CM. This underlines the focus in core CM on meta-modeling (e.g., Buchmann et al. 2019), while mental modeling is considered a skill to be developed via science modeling, e.g., model-based learning and reasoning (see above). The results show that, except for core CM and science modeling, these modeling skills are not widely studied, possibly due to a lack of general awareness about the core principles of CM. This is a significant impediment to the unification of CM and the evolution of CM education as a standalone discipline. More knowledge dissemination of these core CM competencies in other CM subtypes is recommended.

We see a general lack of interest in "citizen modeling," which can imply similar principles, as in Sandkuhl et al. (2018) or enterprise modeling teaching (a rarely studied subject). To have higher capabilities, companies must have education systems that support the inflow of capable human resources. As such, we suggest that while there is support for the vision of Sandkuhl et al. (2018), there is still much work ahead to research the cusps between the CM subtypes and natural/citizen modeling, which is done more unmediated.

Mathematical, simulation, and agent-based modeling often co-occur with the core CM and more distantly related CM subtypes, indicating that educational techniques are investigated similarly across several modeling subtypes. Science modeling seems to integrate these types of modeling more than the core CM, which requires additional exploration to understand the underlying reasons.

There is an evident lack of financial, economic, technical, educational, geographic, ecological, role, and citizen modeling in the data sample, meaning either (1) a lack of such studies or (2) a lack of connecting studies to the included modeling types, or (3) a lack of a similar phenomenological basis, or (4) learning techniques applied are different. For example, financial and economic modeling has a low co-occurrence with business-oriented modeling types, like process, business, and enterprise modeling. In comparison, technical modeling would have more co-occurrences with IS or science modeling. It may also be based on a false presupposition that CM is "only limited to IT departments and not done by citizens everywhere" (Recker et al. 2021). Hence, we observe another research gap: a lack of research focus on citizen modeling. The analysis presented in Table 4 identifies the core CM cluster, encompassing conceptual, software, IS, UML, data, and enterprise modeling, as the most prominent. (Business) process modeling emerges as a distinct basic theme, and clusters like science education, model-based reasoning, and mental modeling highlight niche areas. Across these clusters, learning topics such as e-learning, formative assessment, and computational thinking suggest pedagogical methods adaptable to various CM subtypes. This thematic map guides future research toward enhancing educational strategies across the CM landscape.

Future research in CM education should traverse several vital areas: integrating less-studied CM subtypes like mental and ecological modeling with scientific modeling for interdisciplinary curricula development and examining the synergy between core and non-core CM subtypes, such as simulation and agent-based modeling, to move towards a more unified and systematic CM educational curricula. Addressing the underrepresentation of enterprise, business, user, and ecological modeling is crucial, as is exploring the potential of technical core CM, like data modeling, to improve process modeling methods. Moreover, incorporating simulation and agent-based modeling into CM education could deepen the comprehension of complex systems.

7.3 Applying and Transferring Learning Approaches Across CM Subtypes

The concept of cross-pollinating ideas among CM subtypes offers intriguing possibilities for educational theory and practice. Drawing from the automatic content analysis (Sect. 4.8) and the heatmap (Fig. 9) concerning learning paradigms, our observations reveal that constructivism is the most dominant learning paradigm, followed by cognitivism and behaviorism. This picture generally resembles state-of-the-art in learning science literature. Some universally applied theories and approaches across CM subtypes are using learning objectives, active learning, e-learning, scaffolding, game-based and gamified learning, project-based learning, formative assessment, and experiential learning. We detail the extensive use of various active and interactive learning techniques across different CM subtypes, highlighting the prevalence of methods like scaffolding, problem-based learning, and model-based reasoning, particularly within scientific modeling contexts. The fashion for such can be based on supportive empirical evidence in their favor. Alternatively, it could be due to the researchers not acknowledging or lacking the expertise required to bring in other theories. For instance, we found a significant gap in incorporating some foundational factors, such as Bloom's taxonomy, the zone of proximal development, and emerging learning theories, such as ubiquitous and mobile learning, suggesting a potential area for further integration. More recent (and more niche) paradigms of connectivism and humanism are also missing.

Future research in CM education should explore the integration and application of various learning paradigms and theories across different CM subtypes since they are discussed to be relevant in learning science in general (Wu et al. 2012; Rosenthal et al. 2019; Cope and Kalantzis 2017). A diversified application of the applied learning theories could foster more robust educational strategies, potentially leading to innovative teaching practices and a deeper understanding of CM's role in learner development across disciplines.

Our observations indicate that publications that do not mention learning theories explicitly originate from the tendency of learning researchers to falsely assume that they can use commonly used mental registrars and terms (like understanding and knowledge) as if they were common knowledge (Taber 2013). The papers that mentioned collaborative learning as an author's keyword did not explore the subject to a significant extent, and this could be both a limitation of a method and a bias of the authors, who could be more conscious of consistent terminology in their papers, as mentioned by Rosenthal et al. (2019). Hence, we recommend that researchers critically reflect assumptions of the theoretical paradigm and concepts pertaining to knowledge, learning, and understanding (e.g., Taber 2013).

We also observe theories that are intensively studied in one or related groups of CM subtypes and rarely or not in others, like model-based inquiry and reasoning in science modeling and learning objectives and active learning in IS, science modeling, and CM. In addition, based on literature, gamified and game-based learning are not studied nearly as often as might be expected (Rosenthal et al. 2019). Thus, we identify research gaps in CM education worth exploring, given that CM subtypes can have similarities in teaching and may benefit from findings in related CM subtypes.

The analysis reveals dominant constructivist and cognitivist paradigms in CM education, emphasizing knowledge construction and advancing cognitive processes, as well as e-learning and blended learning approaches. Using e-learning, blended learning, educational technologies, intelligent tutoring systems, and formative assessment (see Table 4, 6, and Sect. 4.8) are prevalent in CM education. Thus, this follows the e-learning ecologies paradigm called by Cope and Kalantzis (2017). It is a non-surprising trend that can be clearly understood as an underlying tone. For instance, Ulrich et al. (2023) explored the use of automated assessments to support teachers in providing formative evaluation to students as they model. Equally, modeling tools and prototyping (Table 4) can represent the role of adapting UI and modeling tools to fit the learning process. Notably, the connectivist paradigm, which emphasizes the social distribution of knowledge and the mediating role of technology, is remarkably underutilized despite the collaborative nature of CM. This gap suggests an opportunity to investigate how consciously employing connectivist strategies (which are already being adopted) could enhance CM education, particularly in an increasingly digital and networked learning environment.

Science modeling has a pedagogical approach of model-based thinking, inquiry, and learning, which is used to unite the students' conceptual understanding across the science subjects (physics, chemistry, biology). At the same time, business and IT education lacks such an educational outlook. We strongly suggest that applying model-based thinking, inquiry, and learning to various business and IT topics could serve as a useful tool to unite the conceptual understanding of the business and IT students and as a unifying theory to unite the learning approaches of CM education. Model-based engineering and management of processes (Verbruggen and Snoeck 2021) has already proven a practical methodology and may be used in business and IT education. To this, research in CM education, such as Panach and Pastor (2023) in the course design, may be recommended for researching how to deliver competencies required for model-driven engineering and development, likely in light of model-based thinking from science modeling.

The theory of p-prims, which explains cognitive tendencies to perceive the world through phenomenological biases, has been effectively applied in science education to understand how students often misconceptualize scientific phenomena (Taber 2013). Similarly, these cognitive frameworks could elucidate common oversimplifications in conceptual modeling education, such as the misconception that all modeling can be accomplished using a single language or that conceptual modeling is merely a subset of software engineering (Buchmann et al. 2019). Such oversimplifications might be attributed to the primacy effect, where students prioritize information that is introduced first and often mistakenly associate it solely with specific domains, such as software engineering. Understanding these biases can clarify why students in science modeling might exhibit greater adaptability in transferring modeling knowledge across different scientific disciplines. This example underscores the potential for theories like p-prims to be adapted across various CM subtypes, enhancing educational strategies and student understanding across disciplines.

Our understanding of the targeted skillset and learning objectives is limited to keyword-based analysis. Even so, there, we could draw on some defining characteristics. Firstly, based on the learning theories, we observe a preference for experiential, gamified, active, project- and problem-based learning. We thus would expect CM education to lean towards applied rather than theoretical approaches. This could have its advantages and disadvantages. As for the advantages, it can mean a more practical skillset that seeks to model per need, and thus, it could supply a high number of workers who would be primarily interested in modeling. On the other hand, a lack of focus on theoretical and conceptual understanding may decrease the number of academics in the field. It may hinder expert conceptual modelers, who may need both applied and theoretical understanding, for instance, to do CM engineering activities, like creating a new modeling language.

Tables 3, 4, and 6 also shed a little light on how modeling learning should occur and the expectations. We can observe endorsement and summarize the overall picture as that of model-based thinking of other disciplines where modeling is applied (science, business, IT), cooperation and thus communication (likely, with the models), promoting systems-wide thinking, inquiring about the problems of the modeled space and concepts and critical thinking, promoting argumentation and conceptual understanding by students. Table 3 presents an idea of using visualization, model-driven development, and abstraction in "core CM," and science/conceptual modeling often studied with problem-solving, argumentation, programming thinking, and the nature of science.

Our findings can hint at the necessity of a visually clear approach to help students develop their problem-based and critical thinking faculties with the models often as mediators into science. Generally, model-based learning and the promotion of inquiry-based learning and reasoning can become critical as students inquire into the principles of CM, which can be heavily context- and domain-dependent. Simulating teachers via cognitive apprenticeship can give a hands-on practical component, which is crucial as students learn a new modeling notation. Argumentation skills can be transferable and meta-level because of CM. Conceptual understanding can refer to understanding both the metamodel and conceptual models' concepts. Systems-wide and computational thinking are both types of thinking required when modeling a system or trying to simulate the conceptual model of a system. Future research should consider exploring the modeling skillset further, as it is perceived from the literature. Based on these findings, learning objectives can provide a suitable framework for the course's instructional design.

The findings extend those stressed by Rosenthal et al. (2023): the need for integrating theoretical knowledge with practical application, critical thinking, and reflective practices to create high-quality conceptual models. Furthermore, the findings can be combined with Soyka et al. (2023), who proposed eight major task classes with 16 specific task types, ranging from theoretical questions to complex case studies, to move toward a coherent taxonomy of learning objectives and competence in CM education with the best learning approaches to develop these competencies.

7.4 Extending and Transferring Research Methods in CM Education

The co-occurrence heatmap analysis (Fig. 4) in Sect. 4.3 reveals intriguing patterns in applying research methods within CM education. Frequently used research methods in CM education include case study analysis, survey research, design-based science, course design, experiments, observations, the use of assignments, qualitative methods in general, and teaching guides. Such empirical, qualitative- and design-driven methods contribute to an empirical basis for understanding an essential component of the instructional design of the CM education field. After all, we find that CM education seeks to apply existing theories of CM to promote the learning results and then report on them. However, we expected that more case-based (course/instruction) design and interpretive methodologies would be prevalent, where educators primarily take the role of *designers* (Dousay 2018).

Rarely used methods are commentary, learning analytics, mixed methods, non-empirical, action research, the Delphi method, longitudinal analysis, quantitative analysis, the use of panels, and neurocognitive-based research (e.g., EEG), eye-tracking, and literature review (except for in science modeling).

Missing longitudinal research indicates a lack of verifying long-term results beyond cross-sectional impact. It is a severe threat to the validity of the CM education discipline, along with the general lack of developed and validated (learning) theories. Quantitative-based experimentations offer the opportunity to confirm the learning effects of specific interventions, hence balancing the prevalent qualitative- and design-oriented experiments, which can be used to generate creative setups and research questions for quantitative-driven experiments.

Although traditional qualitative methods like experiments, design science, course design, surveys, interviews, and case studies are prevalent, there is a noticeable dearth of quantitative and physiological data collection methods such as fMRI, EEG, and eye-tracking. This gap suggests a potential untapped reservoir of data that could offer novel insights into the cognitive processes underlying CM. For example, physiological methods could provide objective measures of cognitive load and engagement during modeling tasks, enriching our understanding of how individuals interact with and comprehend various CM types.

Additionally, the scarcity of longitudinal, non-empirical, and theory-building approaches, including literature reviews, points to a need for more in-depth, systemic studies that span over time to capture the evolution of CM education. This could involve the development of new theories or models to understand the long-term impact of CM teaching methods and curricula. To advance the field of CM education, we suggest further theory-building and literature review research or meta-analysis in core CM and all CM subtypes. Future literature reviews driven by qualitative design could consider CIMO-logic, or Context-Intervention-Mechanism-Outcome, as a framework to understand and analyze complex systems or interventions (Costa et al. 2018). The CIMO logic aligns with the objective of conceptual modeling, as both aim to simplify complexity and enhance understanding of intricate phenomena. Current research contains examples of Context logic (see Sects. 4.4 and 4.6.4.) and Intervention/Mechanism logic (see Sects. 4.3 and 4.8). The Outcome component was not covered, possibly due to our quantitative-driven bibliometric research design, which did not focus on specific findings in studies. Future research could refer to the current findings and focus on the broader Context and typical Intervention Mechanisms in CM education.

There is a high prevalence of quantitative methods in science and simulation modeling, focus groups, thinking aloud, theory development, literature reviews in science modeling, and a high amount of empirical research. This may indicate maturity of science modeling education, as it seeks to produce theories and explanations as it ramps up on the empirical evidence. Given the broad application of research methods in science modeling education, future research could explore why this CM type is more conducive to varied methodological approaches, potentially transferring these practices to underrepresented CM subtypes.

Based on the above, considering transferring findings across the CM subtypes, we can suggest a strong call for creating and validating theories on the acquired empirical evidence in "core" CM education fields, along with quantitative methods, to complement the added value of qualitative empirical methods.

7.5 The Context in CM Education Research

The heatmap analysis (Fig. 5) points to a strong focus on higher education in CM research, with vocational and secondary education also standard, while highlighting a gap in research within PhD, primary education, and teacher training contexts. Though less represented, citizen science offers a novel avenue for engaging the public in scientific inquiry and is currently associated with a select few CM subtypes. Future research should thus diversify CM studies across educational levels, particularly at the PhD level, expand CM applications into industry and vocational training, and explore innovative citizen science integration, all while developing new CM teaching strategies tailored to various educational stages.

There are also significant differences between the different CM subtypes. Scientific modeling is a common focus across K-12 education and in higher and vocational education settings. In contrast, core CM tends to be concentrated primarily at the undergraduate and graduate university levels and within vocational training programs. This pattern indicates that students entering higher education to study core CM might be less prepared than their scientific modeling counterparts. This disparity is likely due to a lack of emphasis on core CM in earlier educational stages. Country and cultural context may impact CM education equally, as we observed specific patterns that the researchers should be conscious of.

7.6 Generalism and Specialism in CM Education and with Researchers

Most researchers (up to about 80%) in the sample analyzed are specialists focusing on only one or a limited set of CM subtypes. Educational researchers simultaneously tend to be educators as well. Thus, having specialized researchers may contribute to the problems of students and novice modelers cross-transferring CM knowledge and skills across CM subtypes (Buchmann et al. 2019) or a false belief that CM is "only limited to IT departments and not done by citizens everywhere" (Recker et al. 2021). Students' CM knowledge is often not transferred across contexts and domains (Taber 2013, p.245). This impedes cross-discipline knowledge and idea fertilization (e.g., using teaching techniques from neighboring CM subtypes). We also find that almost all productive authors and co-authoring groups are generalists with at least three, but often four or five publications in CM education subtypes (possibly due to the ability to better understand universal CM and educational principles).

Moreover, on average, every paper addresses two CM subtypes, indicating that most works are interdisciplinary, corresponding to the interwoven conceptual structure of CM education. Hence, we strongly recommend that CM education researchers attain a comprehensive, interdisciplinary perspective on CM and CM education, promoting the richness of public knowledge and allowing teachers and researchers to disseminate the findings more easily across CM subtypes, as there is the need for a common acknowledgment across CM educators of neighboring fields. Science Modeling education seems to be better integrated, and core CM educators should take the example. This paper can provide an initial overview and a step in this direction.

With most authors tending to specialize in one or two subtypes, there is an opportunity to explore the impacts of such specialization on academic careers and research output quality. Conversely, studying the characteristics and outcomes of generalists who engage with multiple subtypes could yield insights into the benefits and drawbacks of a broader research focus. Furthermore, understanding the specialist vs. generalist approach to learning and teaching CM could be a relevant issue, which was largely ignored as a dedicated subject so far, with only recent calls to study modeling in a unified manner (Cabot and Vallecillo 2022; Ghiran et al. 2020). In particular, the misrepresentation of CM as a tool in other disciplines may be associated with the larger specialist mentality among the researchers, who are simultaneously the educators of future modelers by the merit of professorship and research in their subjects. The identified clusters of co-authors and their focus on specific CM subtypes suggest that collaboration patterns might significantly influence research productivity and focus. Future research could delve deeper into how these networks form and their impact on research innovation and dissemination within and across subtypes.

7.7 Practical Implications for CM Educators

Building on the theoretical underpinnings discussed earlier, this section elaborates on the practical implications for educators and teachers engaged in teaching various subtypes of CM, primarily in the context of business and IT education, which aligns with our initial position statement. We assert that CM should be approached with the same rigor as mathematics and statistics in management education. By using these disciplines as benchmarks, educators can more clearly identify the disparities between the current state of CM education and its ideal state, which may be starkly different. Specifically, we argue that (1) CM is not universally accepted as a transdiscipline as mathematics; (2) the capabilities of the students in CM are worse than that of mathematics; (3) CM does not serve as a universal form of communication between disciplines, like mathematics.

Developing CM competencies is crucial and could be highly beneficial across various professional and educational contexts. These competencies are essential for analyzing, planning, and communicating tasks and are integral to most high- and mid-skilled professions. Consequently, CM should be a necessary skill within educational programs, although it may exceed the capacity of a single teacher or course to deliver fully. This suggests a shift towards viewing CM as a cross-disciplinary glue, potentially supported by dedicated courses designed to address this expansive need.

Several papers on CM education do not report on the learning approach employed (see also Rosenthal et al. 2019). Besides being an obvious threat to the validity of the studies and a limitation on derivative research, such as literature research, a lack of explicit reflection on the learning approach can limit the effectiveness of instructional programs in CM. Educators, researchers, and reviewers are strongly encouraged to adopt a more critical stance towards reflecting underlying learning approaches, which are of similar importance as the employed research methodology.

We urge educators to adopt a broad, generalist perspective in their approach to conceptual modeling, even if they specialize in specific subtypes of CM. This broad approach can foster the transfer of valuable ideas across different subtypes of CM, enhancing educational experience. Students stand to benefit significantly from exposure to diverse modeling perspectives and tools, which can help mitigate common modeling biases (Buchmann et al. 2019). This approach encourages student–teacher collaboration and co-learning, fostering the emergence of CM as a distinct discipline that could attract new talent due to such collaborative efforts.

While beneficial, adopting a wide range of perspectives in conceptual modeling (CM) education is challenging. The pragmatic aspect of refining these approaches involves navigating two main risks.

Firstly, the challenge is finding a balance between overly broad and abstract content versus overly specific and narrowly focused instruction on specific modeling languages. A too-generalist approach in CM may lead to overly theoretical learning that lacks practical, tangible applications, which could disengage students by not providing clear real-world applicability. On the other hand, focusing too intensely on a specific modeling language might restrict students' understanding of CM's broader applications and inhibit their ability to apply conceptual modeling principles across different contexts. Educators, therefore, must establish clear boundaries and guidelines within their curriculum. This structure will allow students to explore and learn from their errors, ultimately leading to more concrete and meaningful educational outcomes. Instructors must tailor learning outcomes to fit the specific objectives of each course, ensuring that students gain theoretical knowledge and practical skills that are directly applicable to real-world scenarios. This balanced approach can enhance the versatility and adaptability of students in various professional settings, making their education in conceptual modeling both comprehensive and applicable.

The second challenge is managing a load of CM education in one course versus the educational program, spanning one degree or even several degrees, including mid- and high school. This endeavor may place additional demands on teachers. Incorporating CM as just one module in a broader course could limit the depth of engagement with the discipline. Adopting new learning paradigms, such as those proposed by Cope and Kalantzis (2017), could aid in designing more effective and efficient instructional programs.

8 Limitations, Delimitations, and Threats to Validity

A systematic literature review does not necessarily lead to a complete census of all the relevant literature (Brocke et al. 2009, p. 2207). While there is a lack of widely accepted categorization borders and definitions of CM subtypes, we introduce delimitations (Alexander 2020) on excluding quantitative and technical-oriented modeling types (like mathematical or simulation modeling) for pragmatic reasons and the general lack of an established CM subtype classification scheme. However, they frequently co-occur with core CM or science modeling. The lack of a widely acknowledged and validated classification scheme is a threat to the validity of our research and a research gap that needs to be addressed in the future. This can further translate to a lack of studies pertaining to modeling types that do not co-occur with those included in the search string.

The present research may be biased because we have not found the expected typical sources for CM education. For instance, the search results do not comprise the typically expected: Enterprise Modelling and Information Systems Architectures Journal (EMISAJ), Innovation and Technology in Computer Science Education Conference (ITICSE), and Symposium on Conceptual Modeling Education (SCME). There was only one article from ITICSE. We have also missed the DSML examples and keywords (Karagiannis et al. 2022) in our initial search string construction, which could have been avoided. Certain publications of 2022 were not yet indexed at the time of the final search (early 2023). The literature sample does not include relevant publications from pertinent sources, such as EMISAJ, published in 2022 and 2023. This is a typical limitation of any search retrieval strategy. A further limitation is a lack of trans-disciplinary collaboration, dedicated sources to CM education, and a lack of classification of CM subtypes. We have addressed this limitation by adding the interpretations of our findings in light of the missing articles from prominent sources.

Another threat to validity is the researchers' bias when including and excluding papers. To address this limitation, we introduced intercoder reliability evaluation as a measure (Cheung and Tai 2021). Researchers' bias may also affect the stage of data interpretation. We provide original data and supplementary analysis in the appendices for potential independent analysis. A lack of absolute accuracy in tagging documents with a CM subtype (approximately 96% of documents assigned), research method (about 64%), research context (56%), and learning theory (30%) is another threat to validity. Via a systematic procedure (see Sect. 3.5), we estimate that of the assigned categories, 15% of CM subtypes and 30% of research method and context were false positive or false negative, and 10% of the learning theory was false positive. We managed to retrieve only about 95% of the PDF files of the documents. However, despite the limitations, automatic keyword tagging is a reproducible procedure and avoids the potential threat of researchers' misjudgment and misinterpretation. As put in Literature retrieval (Sect. 3.4); after retrieving the dataset, we know of relevant publications that could have been retrieved but were not with the given literature retrieval process. The retrieval process still yielded many relevant results (typical for other literature reviews in the field). The issue is related to CM education delimitation (see discussion in 5.1 and 5.2) and could be improved in future reviews.

9 Conclusions

We followed the recent vision and calls of unifying CM and attempted this for CM education (Cabot and Vallecillo 2022; Ghiran et al. 2020). To this aim, we performed a bibliometric literature review facilitated with a semi-automatic keyword and content analysis covering 1064 documents from 1982. We have explored how CM education subtypes relate to research methods, context, and learning theories/approaches. We have also analyzed and interpreted conceptual, social, and intellectual structures.

Primarily, we have identified the need to adopt a unifying perspective on CM education, given that several CM principles are universal and can be fully appreciated only via multiple contexts. This trend in research is set in CM

(Storey et al. 2023) and CM education (Buchmann et al. 2019; Rosenthal et al. 2019). The work can be tedious, given the need for multidisciplinary knowledge and approach, but it is rewarding, as generalists are the most productive and cited authors in CM education. Initial steps in this pursuit can begin with tasks such as reaching a consensus on the definition of CM (frequently burdened with diverse interpretations), crafting definitions and delimitations for CM subtypes, and formulating a classification scheme. Such a trajectory extends towards including more comprehensive modeling types, such as mathematical and financial modeling. We provide our vision and perspective as a potential starting point for future researchers.

Many CM subtypes are interrelated, and the literature often claims CM is based on shared principles. However, the intellectual structure indicates that the vast majority (up to 90% of authors) and most productive co-authoring groups have focused on only one or two CM subtypes. Science modeling (as an encompassing modeling type) seems to be more mature regarding the integration of multiple types of modeling (e.g., in chemistry or physics) compared to what we define as the core CM subtypes (including software engineering, enterprise, and process modeling). Meaningful learning occurs when students relate new information to existing conceptual structures (Taber 2013), and we suggest that students would benefit from understanding that modeling business processes is interrelated to the modeling they perceive of atoms in physics. We see that the research and proposed educational programs have only recently started to move in this direction of formalizing and unifying principles of CM education (e.g., see Buchmann et al. 2019; Rosenthal et al. 2019). Such research has tried to advance this cause by proposing ideas (e.g., research methods or learning theories) that can be employed across multiple CM subtypes.

This article further emphasizes the need for maintaining rigorous research practices. It underlines the importance of theory-building and further empirical research approaches (e.g., eye-tracking) that are currently missing, particularly in the core CM education. Furthermore, we advocate a more deliberate approach to the use and reporting of pedagogical theories and encourage the introduction of less commonly used theories, such as connectivism and humanism, which can potentially enhance both theoretical and practical outcomes. Additionally, we call for expanding research on core CM education to encompass pre-college levels, including primary, middle, and high schools, which would arguably facilitate the knowledge transfer for students starting their (under)graduate studies across CM subtypes. We also suggest introducing a more diverse cultural research context into CM education research to enhance the transferability, reliability, and validity of educational findings, given that there is currently a significant impediment to the external validity of the field. This further highlights the need to foster international research collaborations in CM education and proposes the growth of more dedicated publication outlets to facilitate the dissemination of research in this domain.

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