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REVIEW

AI-artifacts in engineering change management – a systematic literature review

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Abstract
Changes and modifications to existing products, known as engineering changes (EC), are common in complex product development. They require appropriate implementation planning and supervision to mitigate the economic downsides due to complexity. These tasks, however, take a high administrative toll on the organization. In response, automation by computer tools has been suggested. Due to the underlying process complexity, the application of artificial intelligence (AI) is advised. To support research and development of new AI-artifacts for EC management (ECM), a knowledge base is required. Thus, this paper aims to gather insights from existing approaches and discover literature gaps by conducting a systematic literature review. 39 publications applying AI methods and algorithms in ECM were identified and subsequently discussed. The analysis shows that the methods vary and are mostly utilized for predicting change propagation and knowledge retrieval. The review's results suggest that AI in EC requires developing distributed AI systems to manage the ensuing complexity. Additionally, five concrete suggestions are presented as future research needs: Research on metaheuristics for optimizing EC schedules, testing of stacked machine learning methods for process outcome prediction, establishment of process supervision, development of the mentioned distributed AI systems for automation, and validation with industry partners.

Keywords Artificial intelligence · Engineering Change · Automation · Engineering Change Management · Machine Learning

1 Introduction

Changes to products are a rule rather than an oddity (Eckert et al. 2004). Without innovating and adopting products, companies risk losing market share and revenue (Balakrishnan and Chakravarty 1996; Eckert et al. 2004). These changes to the behavior, function, or structure of a technical component are generally known as engineering changes (EC) (Hamraz et al. 2013). With estimated costs per change accumulating to 20,000–50,000 € and an average of 1,000 changes per month at a German automotive OEM (Wasmer et al. 2011), the economic implications of EC and its management (ECM) are large. Failing to respond to the challenges has been attributed to costs as high as 30% of a component's price (Iakymenko et al. 2020a), a 20% increase in warranty charges (Capistrano Burgos et al. 2022), and an additional 15% in cost for redesign (Eckert et al. 2004). Within complex industries, such as aviation and automotive, the number of ECs have been shown to have increased in the past (Eckert et al. 2011), a trend which is expected to continue with the shift toward highly iterative product development (Schuh et al. 2018). Since change is inevitable, its efficient handling is a key competitive edge.

However, the EC process is complex and versatile. The process flow is not linear, but iterative (Fricke et al. 2000), with frequent loops and extensive communication in interdepartmental teams (Clark and Fujimoto 2005). Additionally, a change to one component may induce changes to other components, spreading throughout the entire product. This phenomenon of change propagation (Clarkson et al. 2004) and the anticipation of the potential economic impact is at the core of ECM research (Jarratt et al. 2005). Furthermore, from a supply chain perspective, even if an EC affects only one component, it can invoke an avalanche of logistical tasks (Diprima 1982). As a result, contributions to EC and ECM focused on controlling the EC process and managing its complexity (Hamraz et al. 2013).

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Another source of shortcomings for adequate ECM is limited capacity. Occurring ECs have to compete with regular tasks for resources (Wänström and Jonsson 2006), and thus, capacity is too limited to control all ECs adequately (Wänström et al. 2006). Up to 30% of an engineer's capacity (Fricke et al. 2000) and 70% of manufacturing capacity are consumed by EC (Ullah et al. 2016). Furthermore, due to change propagation, it is near impossible for even experienced staff to anticipate all effects of an EC on the finished product (Eckert et al. 2004). The reduced predictability of EC effort is further exacerbated by fluctuations in supply chains (Capistrano Burgos et al. 2022) and the increasing complexity of products (Schuh et al. 2015).

As a response, researchers suggested computational tools to support, anticipate, and automate EC-related tasks. Barzizza et al. (2001) for instance devised an optimization method to calculate stock-optimal effectivity dates, whereas Clarkson et al. (2004) developed computational methods to predict change propagation paths. To augment computational ECM support, research suggests addressing two key challenges: Flexibility due to the complex nature of EC (Liu et al. 2004) and dynamic decision-making due to change propagation (Yeasin et al. 2020) and supply chain uncertainty (Shivankar and Deivanathan 2021). These challenges for advanced computational support of the EC process can be translated to the ability of flexible, human-like decision-making, which is the scientific research area of artificial intelligence (AI). By applying AI, new possibilities to automate EC tasks arise (Zheng et al. 2019), for instance, automatic design adaptations (Sharp et al. 2021) and problem identification (Camarillo et al. 2017). However, these AI-methods are not only capable of support for single tasks but moreover increasingly able to manage and control complex processes (Burggräf et al. 2021). Thus, targeting the future of cyber production systems (Burggräf et al. 2021), it is suggested to automate the entire EC process by researching new AI-artifacts.

Research of new AI-artifacts falls into the domain of information systems (IS), where design science research (DSR) has established itself as the predominant research paradigm (Baskerville et al. 2018). To ensure scientific rigor and equally focus on practical appliance, the DSR framework by Hevner et al. (2004) is commonly used as a guiding methodology (Peffers et al. 2018; vom Brocke et al. 2020). Hence, as IS and ECM research are both rooted in practical appliances requiring scientific rigor, we suggest applying the above DSR framework for future research on AI-artifacts for ECM. Accordingly, these new artifacts should be based on business needs from the environment, supported by a knowledge base from theoretical foundations and available methodologies within the domain. These four business needs for ECM were defined by Radisic-Aberger et al. (2022) as *automation*, *decision support*, *optimization,* and *supervision.* Current literature reviews, however, have not covered how current AI-methods in ECM address these business needs.

Thus, this study aims to establish a knowledge base for research and development of new AI-artifacts for EC control by systematically reviewing published AI-related contributions in the domain of ECM. As a review procedure, we apply the framework for IS literature reviews by vom Brocke et al. (2009). In this context, the necessary knowledge base is built on insights and identified research gaps and incorporates experiences, expertise, and existing artifacts from the application domain (Hevner 2007). Hence, our review of AI-artifacts within the EC domain is driven by two main research questions (RQ):

- RQ1: What insights can be gathered from AI applications in the EC domain?
- RQ2: What future research is necessary for AI-supported ECM?

The remainder of the contribution is structured as follows: Sect. 2 defines the business needs in the application environment of ECM and provides a review of existing literature. In Sect. 3, the systematic literature review method is described before discussing the results in Sect. 4. Section 5 answers RQ1 by providing the insights derived, which are the base for providing the research gaps and answering RQ2 in Sect. 6. Finally, a conclusion and outlook are provided in Sect. 7.

2 Background and related work

To answer the RQs and subsequently establish a knowledge base for developing future AI-artifacts for ECM, two background concepts are described which are later used for organizing the literature: (1) the four business needs identified for EC control and how they are currently addressed, and (2) related EC literature reviews and their framework.

2.1 Business needs for AI-supported processing of engineering changes

Although ECM research is driven by the five overarching goals of *less, more effective, more efficient, earlier, and better* (Fricke et al. 2000), publications along the core EC process focus on earlier, more effective, and more efficient EC handling (Hamraz et al. 2013). The goal of increased efficiency is commonly interpreted as the reduction of EC-related costs (Wänström et al. 2006) and the best use of resources (Iakymenko et al. 2020b). Effectiveness is improved by decision-making support, while earliness is improved by predicting problems before they occur. It is generally recommended to involve downstream process partners as soon as an EC is requested (Ouertani and Grebici 2008). However, decision-making with partial knowledge, lengthy processes, and a multi-departmental environment without visible ownership cause ECs to become a bottleneck process instead of an enabler for product maturity (Potdar and Jonnalagedda 2018). Thus, Radisic-Aberger et al. (2022) suggest research on new AI methods based on four identified business needs which have been simplified to:

- Business need 1: Automation
- Business need 2: Decision support
- Business need 3: Optimization
- Business need 4: Supervision

The first business need targets the main challenges of complexity control and capacity increase, which emerge due to the EC process itself. Past literature mainly resolved the issue with qualitative solutions. For instance, Liu et al. (2004) conclude that the complexity of the EC process requires a flexible workflow system such as Petri-nets, while Bhuiyan et al. (2006) have elaborated that introducing multiple ECs simultaneously as a 'batch' is superior to individual introduction. This batch idea was further discussed by Wynn et al. (2010) and Ahmad et al. (2010) who provide methods to identify optimal frequencies and batch sizes for EC scheduling.

The second business need has been addressed in several contributions by simulations or rule-based methods. Wänström et al. (2006), for instance, suggested a decision tree model for application with various logistic EC variables. Similarly, Li and Moon (2011) provide a model to address company-dependent decision-making suggestions by integrating various data sources. Ouertani (2009) as well as Reddi and Moon (2011) show that predicting the impact of changes is effective for conflict resolution and effectiveness in EC.

Business need 3 is more related to later phases of the EC process, with several publications concerning effectivity date optimization, e.g., (Barzizza et al. 2001; Shiau 2011) and optimal test schedules (Kukulies et al. 2016), but also optimization of change propagation paths (Haibing et al. 2021). Although differing in their goal, the overall procedure is similar: An optimization function is solved for a set of variables and based on the nature and different strategies based on the EC trigger suggested. Lastly, due to the EC process being lengthy and problems occurring unexpectedly (Diprima 1982), the entire process should be monitored dynamically resulting in business need 4.

2.2 Artificial intelligence

AI is a vast research area, composed of six main disciplines along the total touring test: natural language processing (NLP), knowledge representation, automated reasoning, machine learning (ML), computer vision, and robotics (Russell and Norvig 2010). Furthermore, the algorithms developed in AI research are often applied in other domains, which leads to confusion on what is and what is not AI (Bzdok et al. 2018). For our review, we only consider methods as AI, if they fit into the definition given by Russell and Norvig (2010): '*AI is the study of agents, that receive percepts from the environment and perform actions based on them*'. What characterizes AI algorithms from simple input–output algorithms, is the ability to improve performance by receiving feedback on the actions they took towards a specific goal. We give a brief introduction of the algorithms in the discussion section for those algorithms, which are used in ECM. For a discussion of other AI methods, we refer to classical AI literature such as Nilsson (2010) and Russell and Norvig (2010).

The application of algorithms is neither limited to their AI discipline nor the domain of AI. For instance, computer vision often utilizes the ML algorithm convolutional neural networks, NLP approaches employ recurrent neural networks and some algorithms find application in other domains such as data mining (Ertel 2016; Russell and Norvig 2010) or dependency modeling (Kumar and Ratneshwer 2016). Thus, AI algorithms are often not classified by their discipline, but rather by the task, they were initially developed for. For this, Russell and Norvig (2010) classify tasks into five types: Problem-solving (PS); knowledge, reasoning, and planning (KRP); uncertain knowledge and reasoning (UKR); ML; and communication, perceiving, and acting (CPA).

2.3 Related literature reviews and the holistic ECM literature framework

With the abundant amount of data recorded in the EC process, it becomes apparent that AI-supported handling of EC might help control complexity and mitigate the pains in ECM. However, although several literature reviews in the domain of EC exist, none focuses on AI applications. Whereas Jarratt et al. (2011) focused more on standardizing terminology, Hamraz et al. (2013) sorted literature into a holistic framework (Figs. 1, 2), which we are later adapting in Sect. 3.4 for classifying AI applications in the ECM domain. This framework by Hamraz et al. (2013) is especially effective at identifying research gaps in the literature, as it builds on the generalized EC process (Jarratt et al. 2005). Within this framework, group 'A' consists of literature focusing on the pre-change phase, dedicated to minimizing the number of changes. Group 'B' considers literature explaining and developing methods and tools to improve the in-change tasks and processes. Analogous to group 'A', group 'C' embodies research exploring the post-change

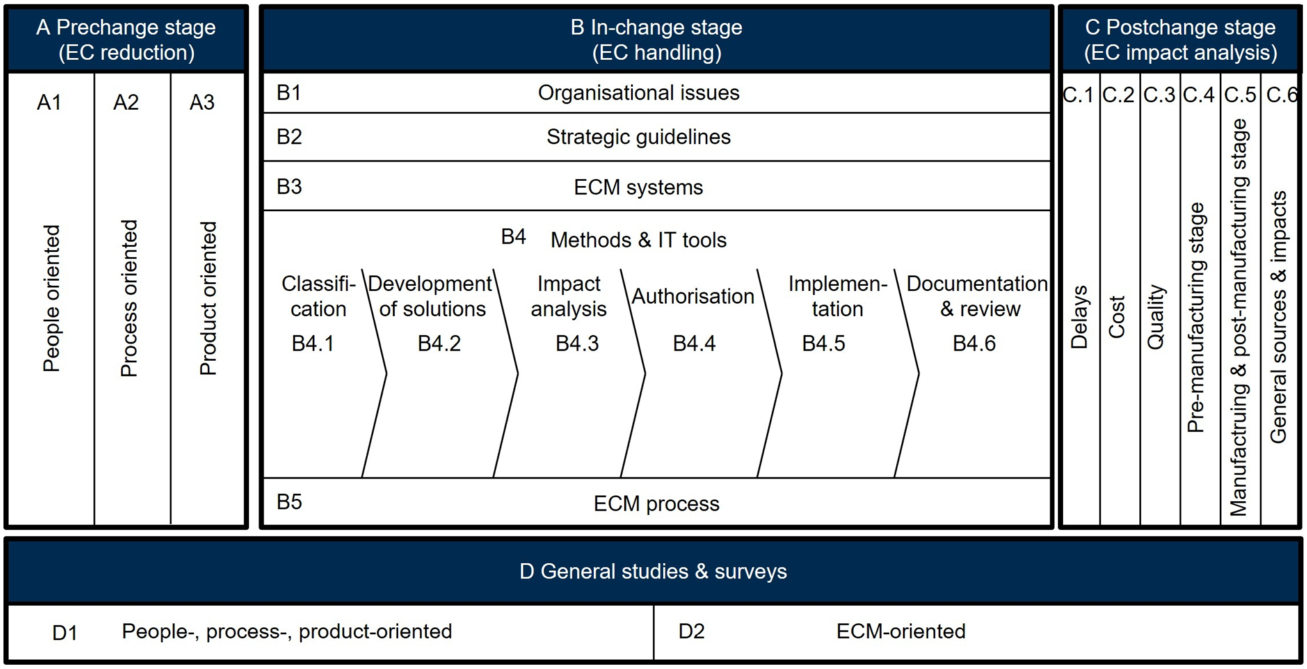


Fig. 1 The holistic ECM literature framework of Hamraz et al. (2013)

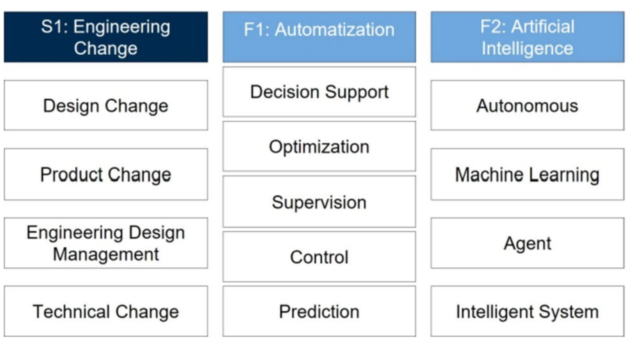


Fig. 2 Conceptualization of the topic according to (Rowley and Slack 2004), with the main search string S1, and screening filter criteria F1 and F2

stage of changes. The residual group 'D' covers publications on general topics and surveys in the field of ECM and related research areas. Additionally, Hamraz et al. (2013) identified groups 'B, 'C, and sub-group 'D2' as the core areas of ECM research, with the others crossing domains with product design and project management.

Most literature reviews that followed afterward are based on one or both major publications described above. Of the seven literature reviews identified after (Hamraz et al. 2013), none discusses AI application in ECM extensively. While change propagation understanding and impact prediction are discussed in (Helms et al. 2014; Ullah et al. 2015, 2016) as well as (Masmoudi et al. 2018), (Tale-Yazdi et al. 2018) is a review on data usage in ECM. Literature reviews focusing on EC implementation discuss the applicability of ECM research in engineer-to-order industries (Iakymenko et al. 2018) or classify EC research towards production, product design, and logistics (Balakrishnan and Suresh 2022). Among the reviews identified, (Colombo et al. 2017) stands out as a meta-study toward standardizing the language used in ECM. Finally, the review on change propagation analysis, its use-cases, and associated data representation by Brahma and Wynn (2022) touched on the application of AI-methods, although they did not discuss AI-methods for other EC tasks.

In conclusion, although several literature reviews have been conducted in the past within ECM, none has widely discussed the application of AI. Hence, to close this research gap and provide a knowledge base for future AI-based research, we present the results of a literature review on AI applications in ECM.

3 Method and Materials

To achieve a reproducible result, a systematic literature review according to the IS literature review procedure by vom Brocke et al. (2009) was conducted. The methodology is split into five steps as follows:

- Defining the review scope (cf. sec. 3.1)
- Conceptualization of topic (cf. sec. 3.2)
- Literature search (cf. sec. 3.3)
- Literature analysis and synthesis (cf. sec. 4)

- Research agenda (cf. sec. 5 and sec. 6)

3.1 Review scope

As our research domain, we focus on EC in the context of goods-producing manufacturing industries. This excludes EC in the context of civil engineering, service industries, and software engineering, as these have essential differences in the production system and separate research streams. Furthermore, we exclude EC for electric circuit layout design. This stems from the extensive literature available in this area, as VLSI layout problem solving via AI has been researched since the 1980s (Russell and Norvig 2010), and has dedicated reviews (e.g., (Singh et al. 2016)).

The scope of our research was further classified according to (Cooper 1988) as an exhaustive review with selective citation, focusing on practices or applications in the ECM domain represented by descriptions of a sample. The overarching goal is a descriptive review of AI literature in the domain of ECM with the identification of central issues, coming from a neutral point of view, with a special focus on EC. It is organized conceptually in a framework (Figs. 3, 4, 5, 6, 7, 8), grouping publications by methodological applications, and targeted toward specialized scholars.

3.2 Conceptualization of the topic

A wide conceptualization of the topic was done to get a broad understanding and an overview of current trends in the scientific community. This step was done by consulting standard literature in the field of ECM, such as books for basic definitions and other literature reviews to identify current ideas. Gaining a broad understanding and looking for synonyms of the topic, a concept map as suggested by Rowley and Slack (2004) was drawn (Fig. 2).

With the key term of search string 1 (S1) being the target domain of 'EC', F1 represents the four business needs introduced before and their respective synonyms. Likewise,

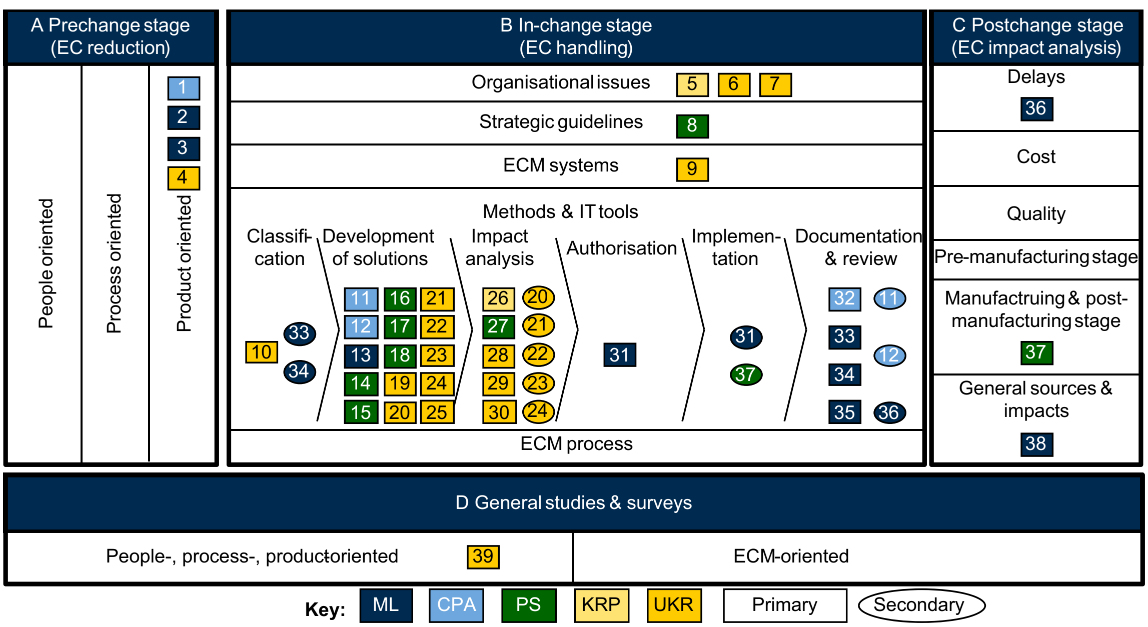
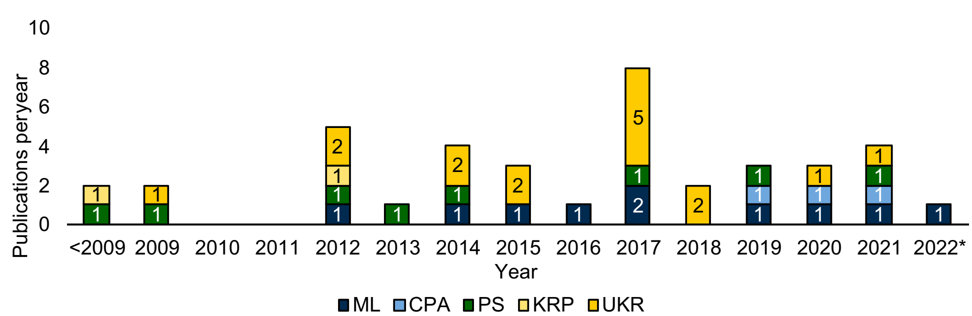


Fig. 3 AI-Literature in ECM clustered by application (primary and secondary) into framework Hamraz et al. (2013) with an additional layer of primary AI-Method employed. The numbers represent the second column in Table 2

Fig. 4 Yearly development of AI based-ECM literature *only the first six months of 2022 are considered



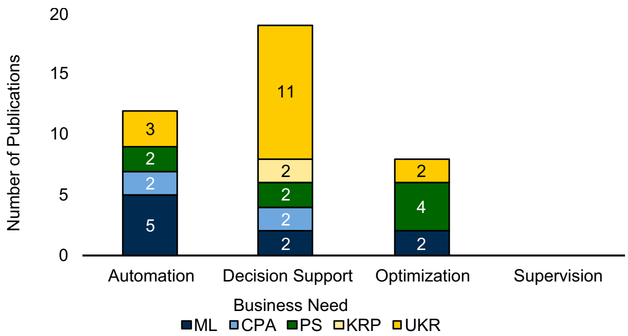


Fig. 5 Split of AI methods in discovered Literature vs. Business Need

F2 embodies the target solution principle of AI. Although Rowley and Slack (2004) suggest applying different combinations of the search strings to discover literature, not all are sensible. Terms F1 and F2 combined, as well as on their own, would result in unspecific general literature outside the target domain, thus, these were omitted. Initially, it was intended to apply only the full combination of the three strings. However, during keyword search of the major databases ‘Scopus’, ‘IEEE’ and ‘WebofScience’, the results were comparatively low (< 100 results for S1 + F1 + F2 and < 250 for S1 + F2), which is why we settled on searching with only string S1 to make sure, that any publication within ECM applying AI-research would not evade the search due to inconsistent wording.

Hence, according to the methodology of Rowley and Slack (2004), the search string was defined as S1: (“Engineering Change” OR “Design Change” OR “Product Change” OR “Engineering Design Management” OR “Technical Change”). The additional strings of F1 and F2 were then used as filtering criteria during the manual screening of titles, abstracts, and the full text.

3.3 Literature search

To identify relevant databases, research by Gusenbauer and Haddaway (2020) was consulted. From their list of databases, we chose those that focus on ‘Engineering’, ‘Computer Science’, or ‘Multidisciplinary’, and have a Boolean search logic and a repeatable search. The result of the initial search is presented in Table 1. To evaluate the relevance of these contributions, quality criteria (QC) for inclusion and exclusion had to be defined. These are, according to the goal and scope of the review (sec. 3.1), and the definition of AI given, as follows:

- QC1: Only journal and conference papers were included. This excludes books and practitioners’ contributions, as the goal was to provide the state of the art in academia.
- QC2: The publication must focus on EC as defined in sec. 1 in the context of manufacturing industries (sec. 3.1).
- QC3: To be relevant, the contribution must discuss the application of AI as defined in sec. 2.2.

Due to language restrictions, only German and English literature is included.

Adhering to the PRISMA (Moher et al. 2010) flow chart (shown in the appendix, Fig. 9), we filtered relevant contributions for deeper investigation. Following the screening of titles and abstracts towards relevancy, 400 full-text entries were kept. After reading these 400 full-texts and applying the QCs, 28 publications on AI application in ECM remained and were considered for further discussion. To ensure we did not miss any publications, we further conducted a forward and backward citation search, based on the discovered 28 publications, as well as previous

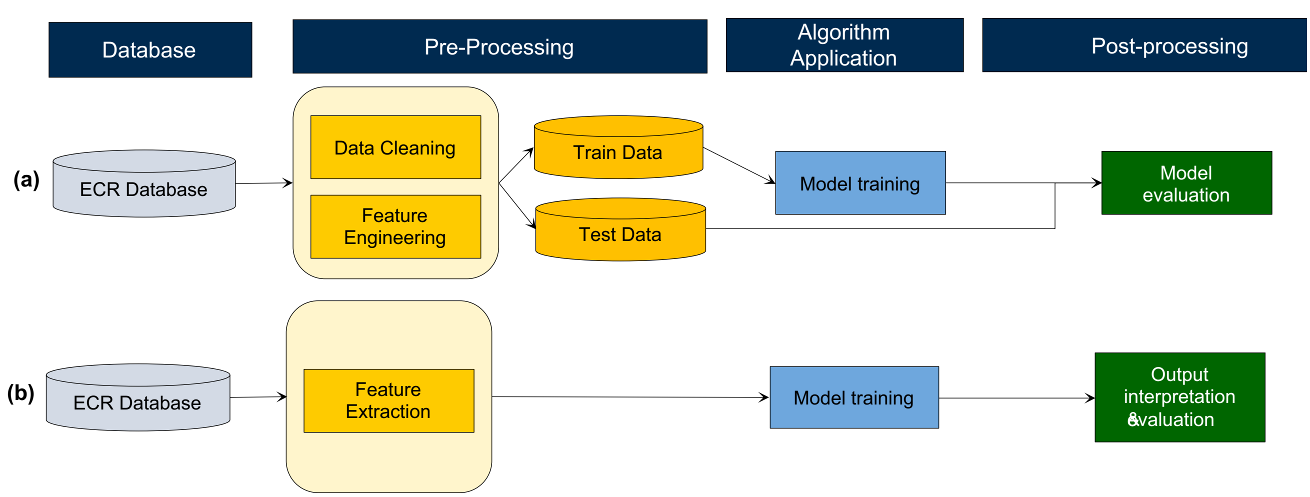


Fig. 6 Typical process for the development of supervised ML (**a**, e.g., Riesener et al. (2021)), unsupervised ML (**b**, e.g., Pacella et al. (2016))

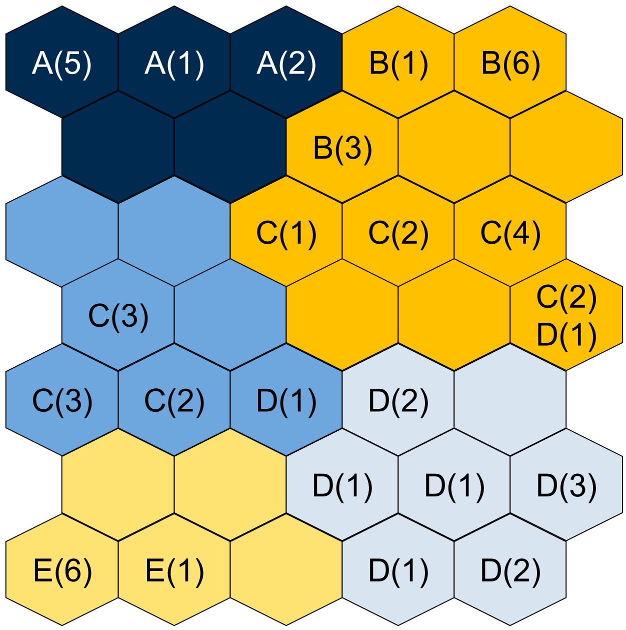


Fig. 7 Example of a self-organizing map adapted from (Pacella et al. 2016). Colors represent clusters, letters the actual label, and numbers how many ECs are within that cluster

literature reviews. As a result, twelve publications were added to the review.

3.4 Organizing the literature

Following the literature search, a three-criteria organizing system as suggested by Webster and Watson (2002) was developed. The criteria (2) and (3) are used for quantitative discussion and criterion (1) for synthesis of future research needs:

1. Primary business need addressed (Table 2, Fig. 5)
2. Primary EC research contribution (Fig. 3)
3. Primary AI method applied (Fig. 3)

With the main goal given as establishing a knowledge base of AI-based applications for implementation of ECs, the presented four business needs were defined as the primary criterion for identifying research gaps (Table 2, Sect. 6). As a second clustering criterion, we applied the holistic framework by Hamraz et al. (2013) (cf. Section 2.3) to give an overview of where along the EC process AI methods are primarily researched and applied. Lastly, we differentiate the publications by primary AI task. To be considered as AI, we take the definition as presented in sec 2.2, and classify them into: PS, KPR, UKR, ML, CPA (Fig. 3).

4 Results and discussion

With the goal of an exhaustive review, the following sections provide the key findings of the literature research. The first section presents a quantitative elaboration of the discovered literature, while in the following section a discussion of each AI method and related AI-publications in ECM is given. Each sub-section first introduces the basics of the given AI-method, discusses how the specific method was applied in ECM, and finally discusses each publication and their conclusions.

Afterward, form this analysis we draw the insights for RQ1 and in Sect. 5 and correspondingly an answer for RQ2 in Sect. 6.

4.1 Overview of AI in ECM

Overall, AI-supported EC methods have been constantly researched, with most contributions being published after 2012 (Fig. 4). As seen in Fig. 3, the focus of general ECM research on the first half of the EC process is also present in AI-based literature, with most publications being published in the areas of solution development and impact analysis.

Of the identified contributions, 49% offer methods for decision support (business need 2), with the rest being split towards optimization (business need 3) and automation (business need 1) (see Fig. 4). Literature focusing on this

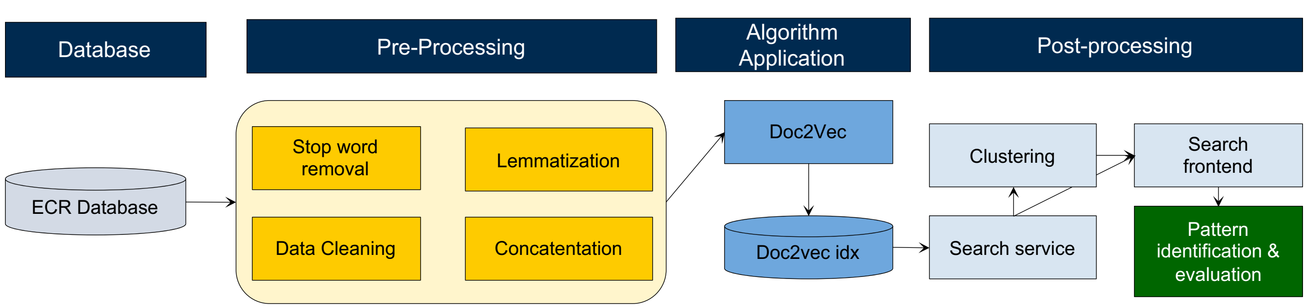


Fig. 8 Typical process for the development of an NLP model application (e.g. (Arnarsson et al. 2021))

Table 1 Overview of search results per database of 26th and 27th March 2022

Data base	Search strategy		
	Keyword	Title	Abstract
ACM digital	65	77	277
Bielefeld academic	378	1109	3969
DOAJ	12	15	90
EBSCO	77	306	1187
IEEE	104	105	420
Science direct[a]		1859[a]	
Scopus	2606	1100	(> 10,000[b])
Springer link[a]		3558[a]	
Web of science	185	205	815
Wiley online	18	23	115
Total			18,675

[a]These databases do not allow for a specific search strategy; thus, the total result is shown

[b]The result was omitted due to no feasible extraction method and no relevance to the topic of EC in random samples, and only the results from S1 + F1 + F2 and S1 + F2 were used

second business need employs various methods, though it UKR methods are dominant, whereas PS algorithms are mostly applied for optimization algorithms. Interestingly, no publication discusses AI approaches to supervise the process (business need 4). This might be due to two reasons: Either the EC process is too complex for supervision by AI applications or the current state-of-the-art is satisfactory enough and there is no need for AI methods.

4.2 Application of machine learning algorithms in ECM

Of all AI research, ML is the most extensively researched subfield (Nilsson 2010). Three main learning approaches exist: supervised, unsupervised, and reinforcement learning (Russell and Norvig 2010). Supervised learning algorithms are often applied for classification or prediction, by learning from input data with known output data (Ertel 2016). Correspondingly, unsupervised learning algorithms find patterns without prior knowledge of the outcome, most often used for clustering (Russell and Norvig 2010). The third, reinforcement learning is mainly used for optimization tasks, based on rewards and punishment (Ertel 2016). Additionally, ML algorithms are differentiated as shallow and deep learning algorithms based on the complexity of their deployment function (Russell and Norvig 2010). Shallow learners require extensive manual data preprocessing (Ertel 2016), an application obstacle circumvented by introducing deep learning algorithms at the price of additional computational cost (Russell and Norvig 2010). As the performance of the algorithms varies depending on the application (Pasupa and Sunhem 2016), a lot of ML-based research in non-AI domains focuses on identifying the best algorithm and data preparation method for a given problem (Bzdok et al. 2018). As with all algorithms, the performance of ML models varies with the preset hyperparameters. Thus, before final testing, hyperparameter optimization runs should be conducted beforehand (Feurer and Hutter 2019). For evaluation of which algorithm and hyperparameter set is best, usually a metric such as the F1-score or AUC-ROC (area under the receiver operating curve) is considered. In general, ML research follows the classic procedure depicted in Fig. 6a, b, supported by methodologies like CRISP-DM (Wirth and Hipp 2000).

From an ECM perspective, 23% of the publications primarily applied supervised or unsupervised learning methods for three business needs (Fig. 5). With a wide range of applications, ML provides support for multiple EC tasks. Out of the nine ML publications identified, three applied ML for change propagation, three for change clustering, and two for understanding ECs and the EC process (Table 2). The remaining publication utilized ML for EC effort prediction. No contribution applied reinforcement learning. Since we classified the publications by the primary nature of the method applied, it shall be noted here that two contributions, (Mehta et al. 2013) and (Chen et al. 2017), used ML as a baseline to compare the performance of their algorithms for impact prediction. These are discussed in the respective sections of their primary contribution.

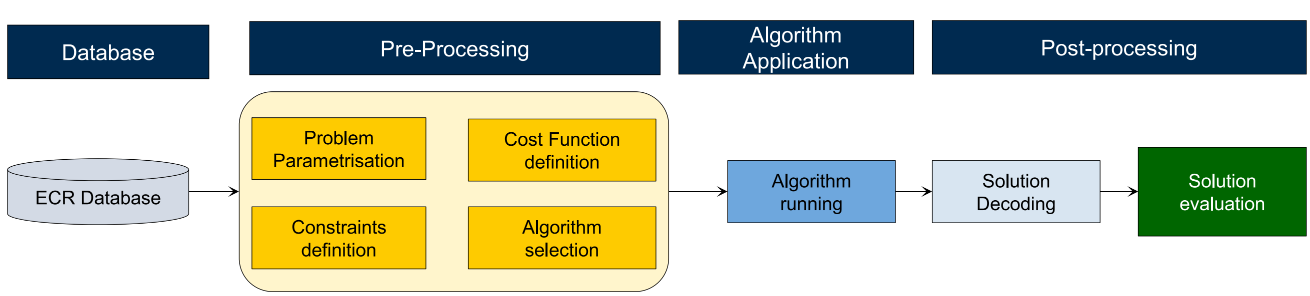


Fig. 9 Typical process for the development of a metaheuristics model application (e.g. (Sharp et al. 2021))

Table 2 Overview on artificial intelligence applications in ECM

Author and year	#	Type[a]	Subfield	Algorithm applied	Goal	Business need
(Koh 2022)	1	CPA	NLP	RoBERTa	EC anticipation	Automation
(Zheng et al. 2019)	2	ML	Supervised ML	Random forest	EC anticipation	Automation
(Morkos et al. 2014)	3	ML	Supervised ML	Artificial neural net	EC anticipation	Automation
(Hu and Carding 2015)	4	UKR	Bayesian network	Bayesian network	Requirements propagation	Decision support
(Chinn and Madey 2000)	5	KRP	Temporal logic	Temporal AI	Workflow optimization	Decision support
(Beroule et al. 2014)	6	UKR	Multi-agent	MAS + Fuzzy logic	Workflow optimization	Optimization
(Sandkuhl et al. 2012)	7	UKR	Fuzzy logic	Fuzzy string comparison	Workflow optimization	Decision support
(Wang and Che 2009)	8	PS	Metaheuristic	Particle swarm optimization	Supply chain optimization	Decision support
(Bender et al. 2015)	9	UKR	Multi-agent	Multi-agent system	Workflow automation	Automation
(Aguwa et al. 2017)	10	UKR	Fuzzy logic	Fuzzy logic	EC prioritization	Decision support
(Arnarsson et al. 2019)	11	CPA	NLP	Document embedding	Knowledge retrieval	Decision support
(Arnarsson et al. 2021)	12	CPA	NLP	Latent Dirichlet	Knowledge retrieval	Decision support
(Pan and Stark 2020)	13	ML	Supervised ML	Random forest	EC detection	Decision support
(Fathianathan et al. 2007)	14	PS	Metaheuristic	Evolutionary search algorithm	Design generation	Automation
(Sharp et al. 2021)	15	PS	Metaheuristic	Genetic algorithm	Design generation	Automation
(Li and Zhao 2014)	16	PS	Metaheuristic	Genetic algorithm	Change propagation	Optimization
(Li et al. 2019)	17	PS	Metaheuristic	Genetic algorithm	Change propagation	Optimization
(Lian et al. 2017)	18	PS	Metaheuristic	Cuckoo search	Change propagation	Optimization
(Camarillo et al. 2017)	19	UKR	Multi-agent	Multi-agents system + CBR	Solution finding	Automation
(Habhouba et al. 2009)	20	UKR	Multi-agent	Multi-agents system	Design evaluation	Automation
(Lee and Hong 2017)	21	UKR	Bayesian network	Dynamic Bayesian network	Change propagation	Decision support
(Ma et al. 2017)	22	UKR	Multi-agent	Multi-agent system	Change propagation	Decision support
(Mirdamadi et al. 2018)	23	UKR	Bayesian network	Bayesian network	Change propagation	Decision support
(Yeasin et al. 2020)	24	UKR	Bayesian network	Dynamic Bayesian network	Change propagation	Decision support
(Diallo and Zolghadri 2018)	25	UKR	Bayesian network	Causal Bayesian network	Change propagation	Decision support
(Mehta et al. 2012a)	26	KRP	First order logic	Own algorithm vs. statistical	Impact prediction	Decision support
(Mehta et al. 2013)	27	PS	Metaheuristic	Own algorithm vs. decision tree	Impact prediction	Decision support
(Chen et al. 2017)	28	UKR	Prob. knowledge	Own algorithm vs. KNN	Impact prediction	Decision support
(Kindsmuller et al. 2014)	29	UKR	Fuzzy logic	Fuzzy logic	Impact prediction	Decision support
(Mehta et al. 2012b)	30	UKR	Prob. knowledge	Own algorithm vs. KNN & SDA	Impact prediction	Decision support
(Riesener et al. 2021)	31	ML	Supervised ML	Random forest	EC effort prediction	Decision support
(Riesener et al. 2020)	32	CPA	NLP	Latent Dirichlet	Change clustering	Automation
(Grieco et al. 2017)	33	ML	Unsupervised ML	Self organizing map	Change clustering	Automation
(Li et al. 2017)	34	ML	Unsupervised ML	Dendritic neural net	Data preparation	Automation
(Pacella et al. 2016)	35	ML	Unsupervised ML	Self organizing map	Change clustering	Automation
(Sharafi et al. 2012)	36	ML	Supervised ML	10 algorithms	EC understanding	Optimization
(Wang 2012)	37	PS	Metaheuristic	PSO + Genetic algorithm	EC scheduling	Optimization
(Lu et al. 2015)	38	ML	Unsupervised ML	Self organizing map	EC understanding	Optimization
(Damak et al. 2021)	39	UKR	Bayesian network	Bayesian network	Flexible design	Optimization

[a]AI method and research field

ML machine learning, *CPA* communicating, perceiving, and acting, *PS* problem solving, *KRP* knowledge, reasoning and planning, *UKR* uncertain knowledge and reasoning

4.2.1 Supervised machine learning application

In ECM, supervised ML has been used to predict EC propagation based on information available from upstream processes (Morkos et al. 2014; Pan and Stark 2020; Zheng et al. 2019), for EC understanding (Sharafi et al. 2012), and for predicting the EC effort (Riesener et al. 2021).

The three publications discussing ML application for change propagation did so at different stages of the EC process. Zheng et al. (2019) tried to predict necessary ECs based on feedback from sensors of smart products, essentially triggering new ECs. Similarly, Morkos et al. (2014) applied an artificial neural net, to predict ECs based on requirements changes. Only the publication by Pan and Stark (2020) applied ML for change propagation prediction during the EC process.

As the overall focus of the publications varied, so did the application depth. As Zheng et al. (2019) conducted a feasibility study, their research did not compare to any baselines and focused more on describing and investigating whether ML can be applied for generating EC requests. The research by Morkos et al. (2014) was on a more mature level. Consequently, as they already knew classical linguistic methods were applicable, they focused on comparing how ML performs against these classical methods. They showed that, although the semi-automatic linguistic approach performed best, the fully automatic application of artificial neural nets could result in similarly good results, without any manual input. Finally, Pan and Stark (2020) focused on which multi-label prediction method was best and developed a better performing hierarchical classification approach.

As all approaches applied shallow learning algorithms (random forest by Zheng et al. (2019) and Pan and Stark (2020), one-layer artificial neural net by Morkos et al. (2014)), they all required extensive data preprocessing. As Morkos et al. (2014) and Pan and Stark (2020) utilized full EC requests as input data, NLP-methods such as the 'bag-of-words' algorithm were required for data preprocessing. Although Zheng et al. (2019) did not specify the data preprocessing, the resulting co-occurrence design structure matrix (DSM) was based on product sensor (e.g., location, temperature) and stakeholder (e.g., visual and natural language) data, indicating that some sort of NLP was applied. However, from an ML approach, basing the data input for the ML-algorithm on DSM seems counterintuitive, as a major benefit of ML is the ability to generate predictive models by feeding data directly without knowing the underlying dependency between the features (Bzdok et al. 2018). In their conclusion, they even remark that basing their approach on a DSM is a major limitation, as it cannot handle incomplete case data, and suggest further investigation for actual data-driven ECM.

A second application of supervised ML was understanding the underlying factors of EC lead time. For that, Sharafi et al. (2012) performed an analysis of ten different algorithms within the supervised ML toolset to empirically derive the main drivers for long lead times. For that, they initially conducted an association rule analysis (a data mining algorithm), which was then used as input for their ML models. Of the 10 algorithms, none was performing significantly better at predicting the lead time. The initial goal of predicting the factors of long lead times was also somewhat unclearly shown. They argue, as the algorithms were able to predict accurately based on product complexity data, that these are factors for long lead times, without identifying their relative importance. This is somewhat at odds with the possibilities of ML. Although it is true that for most algorithms feature importance is not easily extracted, by repeatedly running the algorithms with and with certain features, their relative importance can be shown (Heaton et al. 2017).

The third application of supervised ML in ECM was presented by Riesener et al. (2021), who applied a random forest algorithm for predicting the expected EC effort. They used real-world data to predict the effort needed to implement changes. However, they were only able to achieve a poor fit ($R^2 < 0.5$) and inaccurate predictions, concluding that random forest has its limits within EC and feature engineering is crucial. As this was also an exploratory study, they did not compare how other algorithms would perform. Furthermore, they have not conducted hyperparameter tuning, usually a very important step in ML model development. Thus, the outcome of their research can be only seen as a feasibility study.

Although all publications applying supervised ML conducted their research with real-world test sets, only Pan and Stark (2020) report on feedback from the organization. Following the presentation of results, they report that the models should be tuned towards *precision*, rather than the F1 score, indicating that for their industry partner a correct classification is more important than finding all potential propagation paths. However, they too do not report on implementing the ML model into the productive environment.

4.2.2 Unsupervised machine learning application

From the body of ECM research, four unsupervised ML approaches were discovered, focusing on clustering (Grieco et al. 2017; Lu et al. 2015; Pacella et al. 2016) and preparing data (Li et al. 2021). Li et al. (2021) addressed the issue that DSMs are based on expert knowledge, which causes difficulties when applying them in productive environments. Thus, they designed a dendritic neural network to automatically generate a DSM based on the dendritic neuron model by Todo et al. (2014). Compared to the baseline, their algorithm did not perform better. However, they did show how to apply unsupervised ML to automatically generate DSMs for further application with change propagation methods. Interestingly, opposed to other ML publications, they based their research on a generic bicycle model, instead of a real-world problem. This is an immense benefit, as this enables other research to build on their outcome and compare their performance without requiring real-world data.

The final three applications of ML in ECM are applications for clustering and extracting knowledge through self-organizing maps (SOM). Although all three applied SOM, their motivation varies. The research by Grieco et al. (2017)

and Pacella et al. (2016) applied SOM for classification in case new ECs are drafted. For performance comparison, they evaluated the performance of the ML model using 54 ECs and compared the clustering result vs. expert knowledge (Fig. 7). They have shown that by applying the SOM method, they achieved an F1-score of 0.9 (with 1 being the maximum). However, they have failed reporting on the decision threshold, as well as conducting performance comparisons to other algorithms, thus their publication can also be classified as an explorative study. Note, that both contributions discuss the same research case, which is why there is no difference between the outcome of these two publications.

The research by Lu et al. (2015) also applied self-organizing maps, although for identification of anomalies in ECs and the EC process. Like the previous contribution, they utilized a real-world data set of 9849 ECs and achieved a high accuracy rate of 96%. An important point they raised is the introduction of control and experimental groups for ML model development employing temporal split. In doing so, they ensured that no data leakage into train data occurs, and the performance during testing was comparable to deployment. However, they do not report on whether their approach was ultimately implemented in a productive environment.

4.3 Application of communicating, perceiving, and acting AI-methods

The research field of CPA methods lies at hand: Retrieving information from data in the form of natural texts, images in large databases and learning machines to act upon these (Russell and Norvig 2010). Within the field of ECM, the only primary CPA application is NLP (Table 2), with image processing being only remarked as a possibility by Zheng et al. (2019). NLP is the ability of a machine to interpret human language input and thereby retrieve knowledge from large data bases (Russell and Norvig 2010). For training NLP models an extensive amount of data is required as the possible combination of letters to words are theoretically infinite. Furthermore, as human language is messy, data cleaning methods such as lemmatization and stop word removal are applied during preprocessing steps (Russell and Norvig 2010) (Fig. 8). Once trained, NLP models can, among other applications, be applied for text classification, query response, and knowledge retrieval (Russell and Norvig 2010).

In ECM, four recent publications exist which have primarily applied NLP to advance ECM. The goal of the first three publications (Arnarsson et al. 2019, 2021; Riesener et al. 2020) is to retrieve knowledge from previous ECs, such that mistakes are not repeated. Contrary to their focus on retrieval from past ECs, Koh (2022) applied NLP to evaluate social media comments, and derive future ECs from that. In their method, they follow the approach in Fig. 8.

While the first publication by Arnarsson et al. (2019) investigates whether a document embedding model outperforms an elastic search model, the other two apply a Latent Dirichlet Allocation algorithm to cluster ECs and provide support in knowledge management. Although all conclude that NLP is beneficial from an ECM perspective in retrieving information, they comment that the tailoring of the solution needs to be driven by the applying organization. Furthermore, as the comparison in (Arnarsson et al. 2019) shows, NLP outperforms elastic search only for longer search queries. These observations are attributed to highly individualized processes and language within companies. Additionally, due to applying the model to the EC database of a single company, the results cannot be generalized (Arnarsson et al. 2019, 2021).

As introduced, Koh (2022) applied NLP for extensive mining of information from social media. In their research method, they do not vary so much from the ML approach by Zheng et al. (2019), although instead of applying the RF, they apply the classical CPA by Clarkson et al. (2004). However, as they focus on the application of NLP, they describe the application of NLP in more depth and offer pseudo code. With their approach, they were able to analyze 3665 YouTube comments, pinpoint the components they affect, and derive ECs therefrom. Furthermore, they have shown that their method is not only applicable to the diesel engine they investigated, but also for ‘Car’, ‘Vacuum Cleaner’, and ‘Washing Machine’, suggesting it is applicable to all products.

Furthermore, we do note here that NLP methods are also important for data preparation for other AI-methods, as seen by the ML approach by Pan and Stark (2020) and Morkos et al. (2014).

4.4 Application of problem-solving algorithms

Problem solving via algorithms is a common subfield of operations research or computer science with countless exact solutions for some complex problems (Russell and Norvig 2010; Taha 2017). However, AI research focuses on attempting to build machines that can find these solutions autonomously (Russell and Norvig 2010). For that, AI research devised informed search algorithms known as metaheuristics (MH) (Russell and Norvig 2010). Their main drawback is the inability of knowing whether the solution found is only a *good* solution or the best possible solution (Ertel 2016). They are quick to adapt and find reasonable solutions even for complex combinatorial problems (Taha 2017). MH can also be combined with other AI-approaches. For instance, it is common to use GAs for hyperparameter optimization or as layers in neural networks (Ertel 2016). In principle, all MH application follows the same procedure (Fig. 9): Develop a mathematical model of the problem, run the algorithm for n number of iterations to find new possible solutions, evaluate the solutions, and accept the best-discovered solution as the solution to the problem.

The application of MH in ECM is shared across all business needs, although its frequent with optimization tasks (Fig. 4.). Two contributions for automation (Fathianathan et al. 2007; Sharp et al. 2021) investigated how component design can be parameterized and subsequently design changes generated. Furthermore, MH were applied thrice for change propagation prediction (Li et al. 2019; Li and Zhao 2014; Lian et al. 2017), once for EC shop floor scheduling (Wang 2012), once for impact prediction (Mehta et al. 2013), and once for supply chain optimization (Wang and Che 2009). The most common algorithm applied was the genetic algorithm (GA), an easy-to-implement and flexible MH (Sharp et al. 2021) (Table 2).

The two most notable contributions in this AI subfield in ECM utilize evolutionary-inspired algorithms in feasibility studies for automatic design generation. As a study object, Sharp et al. (2021) demonstrated how GA can be applied for automatic design optimization after an EC is requested. Similarly, Fathianathan et al. (2007) applied a related evolutionary search algorithm to automate fixture changes after ECs. After defining the needs on how to approach the technical optimization problem, both present a simulated case study. In the descriptive depth of their study, Sharp et al. (2021) laid out a detailed automatic EC request workflow, depicted in Fig. 10. Comparatively, Fathianathan et al. (2007) focused more on arguing for and explaining the concept of evolutionary search algorithms. Both together have shown that MH are a possibility to automate parametric design, be it a discrete (Fathianathan et al. 2007) or continuous (Sharp et al. 2021) optimization problem. Sharp et al. (2021) further compared the performance of the MH vs. a human engineer, and although the calculation consumed more time, based on the input parameters the computer algorithm identified a better solution with less monetary resources invested, showing the potential of using AI to automate EC design activities. Fathianathan et al. (2007), however, has failed to show a comparison.

Li and Zhao (2014) as well as Lian et al. (2017) employed MHs to identify change propagation paths for improved scheduling of solution development. Both approaches are not standalone applications of MH, but rather a combination of graph networks and MHs. With their research, they offer methods to reduce change propagation and optimize the duration of the design phase of an EC. A key challenge faced by Li and Zhao (2014) when applying the GA was the inability to a priori determine which design tasks are affected by an EC. As a result, the model had to include all possible paths, irrelevant whether it will be followed, resulting in redundancy. In their follow-up research, Li et al. (2019), they improved

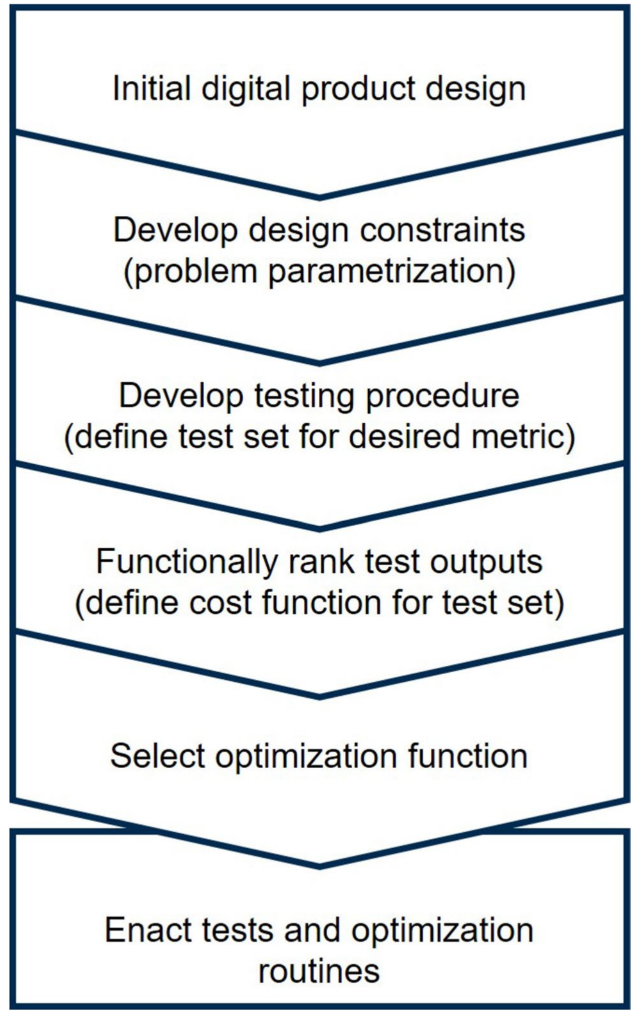


Fig. 10 Automatic engineering change request workflow as suggested by Sharp et al. (2021)

on this method by introducing more constraints, providing an optimal EC propagation path. The publication by Lian et al. (2017) considers using the improved Cuckoo search algorithm, instead of the GA. As with other publications, these three papers present their research based on an exemplary sample but do not compare different algorithms or to other publications, thus they can also only be considered as feasibility studies.

Other MH research for capacity optimization using a GA was done by Wang (2012), who combined it with a Particle Swarm Optimizer (PSO) to minimize customization costs by decreasing the job floor make span time of ECs by optimizing the manufacturing schedule. They showed that a hybrid solution provides better results than using only GA or only PSO, as it enables the algorithms to escape local optima. To further solidify their outcome, they compared the approach to an already established method, which performed worse than any MH application. Overall, their research offers a method to improve the EC realization phase at the shop floor, an often overlooked area in ECM (Hamraz et al. 2013).

Impact prediction by application of MHs was shown by Mehta et al. (2013), who developed an own algorithm based on ant colony optimization, a common MH. Their extensive research shows, how important attributes of ECs can be discovered by MHs and utilized for knowledge retrieval. In their research, they compared their MH approach vs. ML models such as Decision Tree and Naïve Bayes classifiers. They have demonstrated that their approach is significantly better, although they do remark that their test set is comparatively small. This in turn leads to reduced interpretability and generalization of their research outcome. At this point we note that their approach was further tested upon by Chen et al. (2017), which is discussed in the KRP section of our review, in accordance with its primary AI type.

Another MH application was suggested by Wang and Che (2009) for preventive supplier selection concerning the complexities of EC. They applied four variations of the PSO to define the optimal product modification strategy by incorporating supplier data into the model. Not only did they mathematically optimize which EC to implement, but also provide a strategy on how to allocate call-off quantities among four suppliers. The extensive data used incorporated hard data as well as fuzzy data.

A common issue discovered in most PS approaches is the neglection of comparing the developed method with existing approaches and algorithms and testing with only a few test cases. Except for the contributions by Wang (2012) and Mehta et al. (2013), none has tested their approach against existing methods. Statistical significance was only proven in one contribution (Mehta et al. 2013), although even here the authors mention that the test set size was too small. For those studies declared as exploratory studies this is acceptable to a certain degree, however, it does reduce the scientific impact of their outcome. Furthermore, no approach reported implementation in a running environment.

4.5 Application of Knowledge, reasoning, and planning algorithms in ECM

The AI field of KRP centers on the ability of intelligent machines to store knowledge about their environment (Russell and Norvig 2010). This subfield deals with the logical representation of knowledge and lies the foundation of many advanced AI methods (Ertel 2016).

In ECM, logic can be applied for knowledge retrieval as shown by Mehta et al. (2012b), or for scheduling optimization by temporal logic as seen in (Chinn and Madey 2000).

In an initial publication, Mehta et al. (2012b) applied KRP to predict the impact of new ECs by searching for similar ECs among historical data. In doing so, they provide decision support to avoid change effects before they are implemented into the product. This was done by the introduction of an own algorithm tested on several expert knowledge-based simulated data sets and compared to an available statistical approach and two classical approaches (metric space and set-theoretic). They show in their research, that EC similarity is indeed a good indicator for impact prediction, and in doing so, they set the foundations for their more advanced approaches (discussed in sec. 4.4 and 4.6 according to the AI-method). Like their other publications, they compare to other algorithms and include statistical significance tests. However, by basing on a simulated test case, their publication shows only theoretical results. Furthermore, the test set (n = 23) is relatively small (17 train cases, 6 test cases).

Although situated in the domain of ECM, the temporal AI representation researched by Chinn and Madey (2000) was a demonstrator for the AI-method itself in the wider area of workflow management. Nevertheless, their research shows the possibility to improve the workflow of EC during the design phase by scheduling ECs and associated tasks based on urgency, feeding to business need3. However, their research was an exploratory study and mainly contributed to possible new research paths to incorporate temporal relations in scheduling problems. As such, no implementation in practice is reported.

4.6 Application of uncertain knowledge and reasoning approaches in ECM

The concept of knowledge representation is shown in sec. 4.5 mainly consisted of Boolean logic, where the outcome of an agent's actions are deterministic (Russell and Norvig 2010). However, this is not necessarily always the case (Ertel 2016). In some cases, the outcome of a process cannot be definitely precalculated, but only a probability given of a certain outcome (Nilsson 2010). Designing agents that can deal with this uncertainty is the AI-subfield of UKR. From our literature search, we have identified four approaches to deal with uncertainty in the ECM process: Probabilistic knowledge representation, Fuzzy logic, Bayesian networks, and distributed artificial networks.

4.6.1 Probabilistic knowledge representation

We identified two publications integrating probabilistic knowledge in ECM, specifically for impact prediction, the publication by Mehta et al. (2012a) and the subsequent research by Chen et al. (2017).

Both contributions apply probabilistic knowledge representation to predict the impact of an EC. Their research shows, that the similarity of change features of the EC are indicators for predicting the impact of new ECs. To proof, they simulated a test set of 23 ECs, of which a random combination of 17 was used as a knowledge base to predict the impact of the remaining 6. Additionally, as with the previously discussed approach by Mehta et al. (2012b), the size of the test case is too small, which was acknowledged by Chen et al. (2017). Furthermore, their test case is based on simulated data, thus it is not shown that the approaches will also work in a running productive environment. However, this is one of the rare cases identified in AI-based ECM research, where a later contribution (Chen et al. 2017) compares their performance against a previous contribution (Mehta et al. 2012a).

4.6.2 Bayesian networks

As seen by (Li and Zhao 2014), modeling every possible propagation path is a memory-consuming inefficient method. Thus, AI-research has devised Bayesian networks (BN) as a prominent AI method to reduce memory and computation resources (Ertel 2016). Closely related to probabilistic knowledge representation, BN are a systematic way to represent probabilistic relationships. They are directed acyclic graphs, where each node connects parents and children with a conditional probability distribution (Russell and Norvig 2010) (Figs. 11, 12).

In ECM, BNs are generally used for impact and change propagation analysis to provide decision support (Table 2). In our literature search, we identified five publications applying BNs which are exclusively clustered into the third EC process step, impact analysis. Most research is motivated by improving the current status quo of the change prediction method (CPM) and DSM. For this, Lee and Hong (2017) and Yeasin et al. (2020) present a dynamic BN (Fig. 8) while Mirdamadi et al. (2018) designed a Bayesian belief network. Additionally, Diallo and Zolghadri (2018) provide

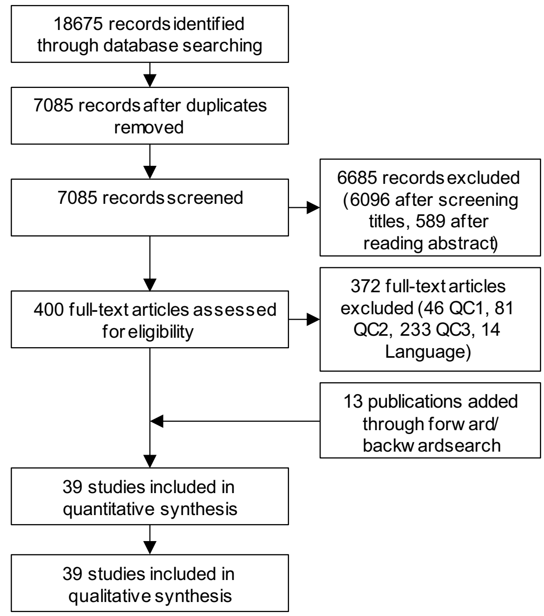


Fig. 12 PRISMA Diagram according to Moher et al. (2010)

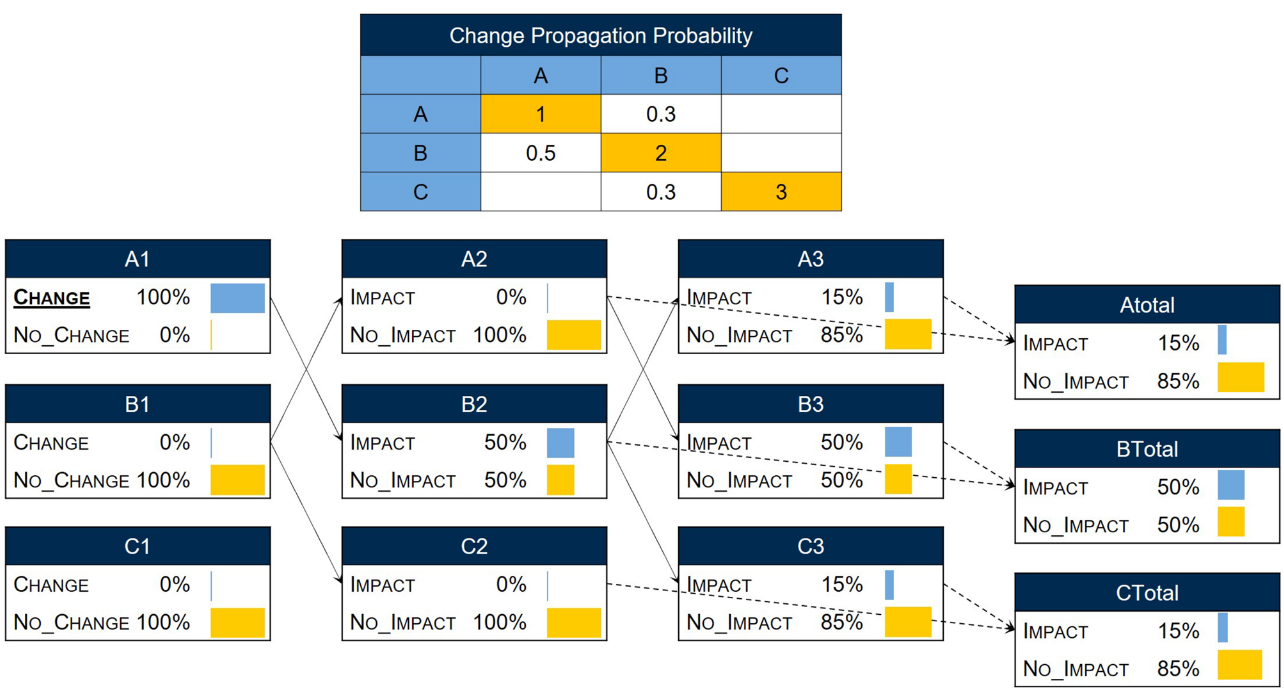


Fig. 11 Example of the change propagation model based on dynamic Bayesian networks by Yeasin et al. (2020). The table above shows the corresponding DSM

a concept for a causal Bayesian network. However, only the two dynamic BN were tested on a data set against the classic CPM. The main benefits of change propagation prediction by BNs were reported to be additional flexibility and, in the case of dynamic BNs, incorporating time effects. Unfortunately, later research has not compared the performance to previous BNs. Furthermore, Diallo and Zolghadri (2018) propose hybrid networks to manage discrete and continuous variables.

Within the discovered publications, two more BN applications have been discovered outside the core EC process. Damak et al. (2021) apply BNs to predict what type of EC an operational change would trigger. This is similar how requirements changes would trigger an EC and the application by Morkos et al. (2014). Thus, their approach is more suited for estimation of effects before an EC is initiated, rather than to support the EC process.

Another goal of EC research and associated field is the prevention of changes (Fricke et al. 2000). One way of achieving this is by designing components in a way, that they absorb changes (Eckert et al. 2004). To determine which components should ideally be flexible, Hu and Cardin (2015) developed a BN-based method. Although they show that it is possible to determine which components should have increased flexibility to absorb potential future requirement changes, their approach cannot address the cyclic dependency. Thus, they suggest dynamic BN for change propagation prediction, as shown by the publications presented above.

4.6.3 Fuzzy logic

An early approach for AI was rule-based logic methods (Nilsson 2010; Russell and Norvig 2010). However, one downside of these systems is that data is usually not available as a Boolean. Hence, fuzzy logic has been devised (Russell and Norvig 2010), and although it is today mostly researched as part of control systems research (Ertel 2016), for completeness we include it as an AI-method applied in ECM.

In ECM, fuzzy logic has been applied for instance to translate requirements by Aguwa et al. (2017), workload assigning (Sandkuhl et al. 2012), and effort optimization (Kindsmuller et al. 2014).

A difficulty when designing new ECs is the prioritization of work, as it is rarely known which EC is most important (Wänström et al. 2006). This becomes even more difficult when ECs are triggered by quality issues (Aguwa et al. 2017). In these cases, the warranty costs per case and the relative occurrence of these indicate a priority. However, interpreting and setting a rule for that requires fuzzy logic, as shown by Aguwa et al. (2017).

A standalone method for automatically assigning ECs to the correct change manager was developed by Sandkuhl et al. (2012). In their approach, they constructed weighted graphs based on fuzzy string comparison to cluster ECs and the respective user. Although their approach is valuable, they mention as their main limitation that it was not validated with a running real-world case.

Another publication considered modeling the product development process to optimize the required effort (Kindsmuller et al. 2014). To do so, they translated errors occurring during development into a fuzzy expert-based model and simulated how the effort is affected by product maturity. They showed, that while software tests are more beneficial in early project phases, hardware tests require a minimum project maturity to justify their effort.

4.6.4 Multi-agent systems

For some complex problems, such as the EC process, the actions of a single agent can depend on the actions of another agent within the same environment (Russell and Norvig 2010), or it is simply easier to model effects (Wooldridge 2003). These systems are known as multi-agent systems (MAS), falling under the subfield of distributed AI systems (Wooldridge 2003). A key concept of MAS is the target for each agent to improve its performance measure, which is not necessarily a shared goal (Ertel 2016).

Within the body of knowledge, five agent-based AI applications were discovered, of which three are utilized to automate EC tasks (Bender et al. 2015; Beroule et al. 2014; Camarillo et al. 2017), one to simulate change propagation (Ma et al. 2017), and a design evaluation (Habhouba et al. 2009) (Table 2). The motivation for all agent-based approaches is to enable the researchers to connect multiple knowledge bases while retaining retrieval speed and manage EC complexity. In their realization, each MAS is highly individualized, which is why these five publications are introduced individually.

Camarillo et al. (2017) developed an MAS for problem-solving from a product quality perspective. By applying a domain-independent agent architecture, they digitalized the existing process at the industry partner for their agent system. Through adding an agent for each specific task and machine they were able to manage the complexity resulting from the manufacturing process. The system was subsequently tested and implemented at an energy storage production facility, and it showed that 80% of the solutions were sensible, and for another 10% the discovered proposal led to a better solution. One of the few publications discussing the implementation of the prototype in a running environment, they state that the availability of proper product lifecycle management and manufacturing problem solving is paramount.

Finally, for data handling automation Bender et al. (2015) compared four agent architectures for combining product and logistics-related data for more efficiency in product life cycle management systems. Their publication remained a concept, although it shows how specific tasks in ECM can be outsourced to the machine, and offer the architecture for other, similar applications.

In some cases, an EC is not a new design, but a recombination of already available components. For this case, Beroule et al. (2014) devised a consensus-seeking MAS of distributed fuzzy agents to integrate multiple departments and generate new combinations of components to resolve EC requests. They show the performance of this method by a simulated example of an office chair. However, they do not compare their performance to a human engineer or other algorithms. Rather, they just state that it is a possibility for automation.

Another MAS application for automation is presented by Habhouba et al. (2009). Having identified that ECM data is too varied to be processed by a single entity, they suggest dividing EC process into its subtasks and devising an agent for every single one. They present a simulated case study of an airplane wing EC, showing the inner workings of the MAS. The final decision of the design, however, still lies with the human expert. From an application perspective, the split into multiple agents has a second advantage, overlooked by the researchers. With distributing the task into many sub agents, maintainability of such a system would be increased as the improvement of each agent could be done independently of the others.

Adding to business need 2, Ma et al. (2017) apply a MAS to model and simulate the effects of ECs and provide decision support. In their work, they described ECs on components as agents, traversing a graph and simulating how changes to a component affect other components. A key component of their method is the inclusion of concurrent ECs, where multiple ECs are triggered simultaneously. In such a case (as seen with the Dynamic BN), ECs on other components have cyclic effects on other components. Furthermore, they increase the level of detail of the propagation analysis by basing their network on parameters and properties of components. Finally, they test their method on the case study of a gear box.

Overall, as all contributions were successful in their respective tasks, they showed that MAS are suitable for computational support of ECM. However, except for the contribution by Camarillo et al. (2017), none of the proposals has reported a deployment into productive environments. Furthermore, it is interesting that no contribution has devised an MAS over the entire EC process. This could relate to the complexity of the EC process, as by Ashby's law (Ashby 1968) to fully grasp it, an equally complex MAS would be required.

5 Insights for future AI-application development in ECM

Insight 1 (I1): Research on AI applications in ECM focuses mostly on pre-approval and post-implementation process steps (Fig. 3.).

AI-artifacts are existent in the field of ECM, although their application mostly focuses on the same areas as general ECM research. There is a high potential for AI application in ECM, going as far as to automate the entire EC process as suggested by some researchers. The main application target is to provide decision support, with a secondary goal to solve capacity constraints or find the optimal design change. The classification of ECs, although only once explicitly mentioned as a goal of AI-research, is often a byproduct of EC impact prediction. This leads to another key takeaway considering the application of AI-methods. The framework chosen shows the primary point of application in the EC process. However, as shown in the discussion of NLP and ML papers, for AI-application multiple process steps must be developed upon. For supervised learning this becomes especially apparent. Without existing labels, no ML-model can be trained. Thus, the last step, documentation and review is an important input parameter for any supervised ML application in ECM (e.g., Pan and Stark 2020; Riesener et al. 2021)).

Insight 2 (I2): Population-based MH and ML algorithms are versatile AI-algorithms for optimizing and automating tasks during the EC process (Fig. 5).

This becomes evident when the range of the applications is considered. Most other AI methods were confined to one or two process steps, whereas ML algorithms cover most process steps. From a usual ML application perspective, it is interesting, that the first two process steps are neglected. As seen in Fig. 3., no publication researched exclusively ML-driven classification of ECs, although it is one of the most common ML applications. This is a direct result of our clustering framework, as only the primary contribution has been considered. Most publications do classify past changes, but mostly as a preprocessing step for other applications, e.g., change propagation. Regarding the development of solutions, we infer that this is due to research occurring in other domains such as design automation, e.g., (Oh et al. 2019; Yu et al. 2019).

Comparably, although MH approaches are concentrated on optimization, they cover diverse tasks within this process step and are often a preprocessing step for ML applications (e.g., hyperparameter optimization). The limiting factor of these algorithms is their design – they always require a cost function, which they optimize their problem with. As such, only those tasks can be automated by MH, where variables can be parameterized, and an optimization goal is given.

Insight 3 (I3): Multi-agent systems are required to fully automate the EC process as the data flow occurring in ECM is too decentralized and the process too complex.

Since research on AI-artifacts mostly focuses on single tasks during the process, full automation can only be achieved by linking them sequentially. However, due to high complexity and EC data coming from various IT-systems and different departments, a specialized solution is required for automating the EC process. In AI-based ECM research, managing complexity is solved by the introduction of MAS. By employing multiple smart agents, data management and maintainability are simplified, and the requirements of distributed stakeholders are fulfilled.

Insight 4 (I4): Within ECM, no standard data set exists to test new algorithms and most algorithm testing is performed on real-world data.

Most publications that tested their approach did so on real-world data. However, as Mehta et al. (2013) point out, to generalize, research on new tools should be done with standardized data sets, which are currently missing in the EC domain. Thus, the results derived from experiments on one data set are confined to the specific case-study, which in turn leads to the necessity to retest algorithms for each company and industry. Furthermore, as these data sets would have a lot of company-specific information, they are probably subject to company secrecy. However, generating a simulated case as a reference set is a double-edged sword. With the simulation, possible anomalies existing within the EC process could be overlooked, or the problem too simplified, leading to wrong assumptions on the performance of algorithms.

Insight 5 (I5): Although most AI research is based on case studies, only a few have reported implementation in the industry.

From all 39 papers reviewed, only one (Camarillo et al. 2017) implemented the prototype in a productive environment, and one (Pan and Stark 2020) discussed algorithm tuning with an industry partner. The reasons for this can be manifold. One major difficulty might be the high individualization of ECM or an insufficient data backbone for AI applications. Other potential challenges are the necessity of consistent data management (e.g., product life cycle management systems) and data access (Camarillo et al. 2017). As a result, AI artifacts are possibly not yet adapted to usage in productive environments, or, at worst, the applicability of the research outcome is not given for productive environments.

Insight 6 (I6): The EC process is driven by expert knowledge and highly individualized, requiring extensive data engineering

As shown by some of the ML methods, the input given by EC requests is often given in natural language. This, however, leads to difficulties. Not only does the language within ECM change in every organization (Arnarsson et al. 2021), but also the EC process itself varies. Thus, any application of AI would have to be tailored to the target organization. The data engineering and mining could further be aided with statistical methods, not necessarily requiring expensive AI methods.

Insight 7 (I7): EC data is mostly vague and the outcome of the process often uncertain, necessitating fuzzy logic and probabilistic methods.

The outcome of any process in EC, be it design generation, change propagation or any other, is difficult to grasp. This is also indicated by the lack of supervising methods (business need 4). This can either be due to the unavailability of performance indicators, or due to inept methods. Any supervision method for the EC process, however, would have to manage this. This necessitates monitoring with uncertainty and probability.

Insight 8 (I8): AI-based ECM Research has seldomly compared their approach to already existing solutions, showing an overall lack of rigor.

A common theme observed was the introduction of new approaches and methods and claiming that they perform well. However, they have rarely compared their approach to solutions discovered in previous publications. This can be a direct result of the high individualization of the EC process (I6), but also due to low rigor in AI-based ECM research. Furthermore, no publication has linked their actual code or algorithm, thus making it difficult for others to replicate the experiments on other test sets. Another general point of critique is the application of AI methods without parameter optimization. Parameters have a significant impact on nearly every AI method, and should always be considered (Feurer and Hutter 2019).

In conclusion, and as an answer to RQ1, the findings from the insights can be described as follows: The complexity and expert-knowledge-based EC process requires AI methods to be applied in an ensemble when targeting automatic EC processing. As most ECs have similarly occurred in the past, using knowledge of past EC occurrences is suggested, although extensive data engineering is necessary. Additionally, we heavily suggest testing new methods against already existing approaches, to determine which method is superior.

6 Implications for Future Research

Following the discussion of results in Sect. 4 and insights in Sect. 5, this section is aimed at synthesizing the outcome and answering RQ2. Resulting from (I1) we have identified that the research gap for EC implementation (Hamraz et al. 2013; Iakymenko et al. 2018) also translates to AI-driven ECM research. Looking at the literature from the perspective of RQ2 and the business needs, we conclude that AI-driven ECM is possible, although numerous research gaps exist.

From the perspective of readily available tools, business need 2 and business need 3 are best covered. For instance, by adapting the clustering approaches of current AI applications towards the first step of business need 3 (Optimization). Further useful methods are the decision support applications defined. As researchers were able to predict the outcome and impact of a change by the usage of EC data (e.g., (Riesener et al. 2021)), the methods could be tested for application during EC implementation. However, this requires extensive testing and data engineering (I4), as the logistical and production data enriches the process. Because of unavailable standard data sets, comparing different approaches is impossible. This can have multiple reasons, such as company policy and data complexity. However, this can be mitigated by sharing the algorithm and code. In doing so, other researchers can test the method with their own data set and compare the performance and improve upon these.

For business need 1, automation of the EC process, research, and development of a dedicated MAS would be necessary (I3). As even more stakeholders are involved during the EC process than during the generation of the design change, the ensuing AI application and agents would have to control various heterogenous aspects.

Hence, an initial start would be to automate those tasks, which are less communication-intensive, like the optimization of the effectivity date (business need 3). This could, in an MAS, be easily done by MH or ML models (I2), while the ordering task is still performed by a human operator. Research would be required on incorporating multiple data sources into the optimization models, as well as defining which MH algorithm is best suited. Likewise, classification and impact analysis could be supported by ML method (I2).

From within our literature review, no direct answer or approach for business need 4 can be derived. However, with (I4) and (I7) in mind, the dimension of the EC process leads to data and information loss on interfaces, causing instability in downstream process steps. Thus, a research gap towards supervision techniques tailored to the EC process becomes evident. Additionally, while other fields of research have explored data needs for AI applications, EC data remains mostly vague (I7). Key challenges remain in mining knowledge from the process and joining various data types together for better process understanding. Future research should therefore also focus on establishing standardized data formatting and data sets, to test newly developed algorithms and methods.

A remaining research gap is a low report on the actual application in the industry (I5). Thus, we suggest conducting case-studies, whether AI-driven ECM has been implemented in various industries. This would further help understand the hindrances and difficulties. Furthermore, without validation in the field, AI applications for research cannot confirm whether their approach is suitable for advances in ECM. Furthermore, several researchers developed new methods, however they have not compared their performance against previously published solutions (I8). This is insofar an issue, as researchers and practitioners alike cannot confirm, which method is best to be applied in industry or case studies. Hence, aiming at RQ2, we can summarize the research needs as follows: While business need 1 requires research on modeling and developing an MAS, business need 2 and 3 have been already addressed partly in the literature. Here, research should focus on determining the relevant factors, and testing various algorithms to determine the best outcome. Eventually, business need 4 would need exploration on AI-driven control of knowledge-intensive processes. To give an overview of future research and the literature gaps, Table 3 presents the business need, how they are currently addressed in the literature, as well as knowledge transfer possibilities from within the domain.

7 Conclusion

Management of ECs increasingly burdensome on design, logistics and production departments. Driven by this industrial need, automation by AI has been suggested by various authors. To aid the development of these new AI applications, we conducted a systematic literature review of publications on AI artifacts in ECM. By discussing 39 identified publications, eight insights and five research needs were documented, thus establishing a knowledge base for future development of AI methods.

In summary, the potential for usage of AI in EC has been recognized by various authors. The most common application is to understand change propagation and change impact. This indicates that most of the problems in ECM emerge from this area. It has been established that conventional approaches are not providing satisfactory flexibility and dynamicity in the EC domain. More so, it is necessary to use different methods from the entire AI toolset, such as NLP, BN, OR, and ML in the ensemble for a fully automatic data-driven EC process. Hence, for full automation of the EC process, an MAS is required.

The two RQs, “What insights can be gathered from AI applications in the EC domain” and “What future research is necessary for AI-supported implementation of ECs”, were answered by presenting eight insights and five research needs, respectively. From the eight insights, in combination with predefined business need, future research on AI-supported ECM should focus on:

(1) Testing of various metaheuristics in the context of EC effectivity date optimization
(2) Testing different combinations of ML methods to predict the EC effort

Table 3 Research gaps of business needs

Business need	Research gap	Transferable knowledge from other AI applications in ECM contribution
Business need 1: automation	Modeling and development of a multi-agent system	(Bender et al. 2015; Camarillo et al. 2017; Sharp et al. 2021)
Business need 2: decision support	Decision support by usage of objective data, unsupervised ML to automatically cluster changes into similar batches	(Pacella et al. 2016; Riesener et al. 2021; Sharafi et al. 2012)
Business need 3: optimization	Metaheuristics approach to define optimal effectivity date	(Sharp et al. 2021; Wang 2012; Wang and Che 2009)
Business need 4: supervision	Constant prediction of outcome of an EC scenario	–
–	Validation in the field by case study, and comparison of different approaches	(Camarillo et al. 2017; Mehta et al. 2012a; Chen et al. 2017)

(3) Researching distributed AI systems for automated EC processing
(4) Development of domain-specific process monitoring methods
(5) Validating AI artifacts with industry partners

With this outcome the review provides two contributions to practitioners and researchers alike: Through providing a detailed analysis of current AI research in ECM, both gain an understanding of the challenges and possibilities already existing in the domain. With a discussion of these insights towards the business need we point towards literature gaps and opportunities for future research in ECM.

As a limitation, we point out that we have restricted the EC definition to technical artifacts in mechanical design and excluded AI-supported EC in areas such as construction engineering, software engineering or circuit engineering. Another limitation of our study is the provision of business need. As these are highly dependent on the implementing organization, the business need presented provide an initial starting point, with the potential for further additions from case studies in industrial environments.

Nevertheless, this review shows a theoretical gap in the field of ECM. To aid organizations with managing design, production, supply chains, and EC, applicable tools for automatic handling of EC are necessary. Future research should thus focus on modeling the EC process and enabling their agent-based realization. This can be done by suggesting optimal effectivity days, automating the EC scheduling task, and supervising the process. Regarding this, AI provides an opportunity. Additional exploration on what algorithms to use is required, and an agent-based approach to model and handle the complexity of ECM should be discussed. Finally, to confirm the theory, the resulting artifacts should be tested with industry partners.

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