Call for Critical and Speculative Design in Human-Computer Co-creativity: An Overview Study

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Abstract

The recent boom of artificial intelligence (AI) and machine learning (ML) has demonstrated their potential to impact human-computer interaction (HCI) in general and human-computer co-creativity in particular. Therefore, we want to provide a systematic literature overview of computational co-creativity research so far. In total, 916 articles from Scopus and Web of Science databases were pulled. Bibliometric analysis of their abstracts and a Latent Dirichlet Allocation (LDA) topic modeling on their full text was conducted to reveal what is covered in the previous academic discussions on human-computer co-creativity. The results of these analyses demonstrate that current research mostly focuses on technology, overlooking the role of design. Accordingly, we call for more design-oriented research to develop a more comprehensive understanding of human-computer co-creativity, especially from critical and speculative design perspectives.

Keywords: computational co-creativity; human-computer interaction; co-creativity; critical design; speculative design; overview study

Introduction

Artificial intelligence (AI) and machine learning (ML) technologies have been part of human-computer interaction research for a long time. Although AI and ML have been frequently used in productivity fields (e.g., auto driving), they have recently demonstrated their capability in creativity thanks to the iteratively optimized algorithms. This newly enabled creativity is, in fact, *co-creativity* as it is a collaboration between human and computational technologies. This evolution gives rise to the current massive interest in generative AI. For example, ChatGPT, made by OpenAI, can generate articles and essays that look as if written by human beings. The performance of ChatGPT was so good that students used it for cheating with their assignments, which seemed to threaten academic honesty (Mitchell, 2022). Other computational co-creativity tools can provide users with automatically generated illustrations based on simple text input (Ma et al., 2022). The adoption of these generative AI technologies into other creative activities seems unstoppable.

Current applications of computational co-creativity (i.e., text and graphic illustrations) are mainly for non-interactive media. Typical use cases include photobashing, text generators, bots, and hypertext fiction tools (Ryan et al., 2018). In interactive media, there are cases using them to create content for text-based adventure games[1], develop massively multiplayer online games (Goncharenko, 2022), and streamline video game development processes (Pérez, 2022). Considering the recent advancement in generative AI and other computational technology in the field of creativity, it is high time for the academic community to have a reflective overview of the human-computer co-creativity relationship. Therefore, we investigate the existing human-computer co-creativity academic research to answer the following questions:

- What are the well-defined research directions in terms of human-computer co-creativity?
- Specifically, what's the role of *design* in current research?

Methodology

We use a systematic literature review to answer the research questions. Following existing guidelines for systematic literature reviews (Kitchenham, 2004), we will perform bibliometric analysis and Latent Dirichlet allocation (LDA) topic modelling. The review is planned, conducted, and reported sequentially.

Data Collection

We collect data by selecting the search strings, the sources to search for, and determining inclusion and exclusion criteria. It is recommended to search academic research publications, archives of magazines and newspapers, and practitioner publications to generate the first versions of keywords related to the topic (Rowley and Slack, 2004). Accordingly, the search keywords are conceptualized to include previous studies on computational co-creativity.

The main interest of this study is **perspectives** on human-machine interaction that have appeared in previous literature. Meanwhile, these perspectives are used to examine recent computational co-creativity **topics**. A keyword matrix is created to indicate how each search is to be conducted by pairing each perspective and topic (e.g., "computer-human interaction" and "co-creativity"). Keywords for our chosen perspective include *computer human interaction*, *human computer interaction*, *human machine*, *human-in-the-loop*,

[1] https://aidungeon.io/

Fields/ Perspective to investigate these fields	“Computer human interaction”	“Human computer interaction”	“Human machine”	“Human-in-the-loop”	“Mixed-initiative”	“User interface”	“Interaction design”	“Creative interface”	“Co-creativity”	“Co-creation”
“Computational creativity”	43	43	96	4	5	25	91	21	12	7
“Generative creativity”	10	10	34	2	2	11	32	7	6	7
“Generative art”	50	50	160	4	1	23	97	6	1	4
“Generative Artificial Intelligence”	24	24	127	2	1	11	33	0	0	3
TOTAL										1089

Figure 1: Keyword Matrix and Number of Results, Web of Science

Fields/ Perspective to investigate these fields	“Computer human interaction”	“Human computer interaction”	“Human machine”	“Human-in-the-loop”	“Mixed-initiative”	“User interface”	“Interaction design”	“Creative interface”	“Co-creativity”	“Co-creation”
“Computational creativity”	142	142	201	5	14	68	160	53	37	20
“Generative creativity”	38	38	69	3	5	35	64	28	15	18
“Generative art”	148	148	405	11	2	71	145	20	3	9
“Generative Artificial Intelligence”	141	141	447	9	7	67	104	13	3	15
TOTAL										3064

Figure 2: Keyword Matrix and Number of Results, Scopus

mixed-initiative, *user interface*, *interaction design*, and *creative interface*. Keywords of topics include *co-creativity*, *computational creativity*, *generative creativity*, *co-creation*, *generative art*, and *generative artificial intelligence*. These keywords may sound arbitrary, but they emerge from the research questions and are grounded in the recently popular and academic discussions on computational co-creativity.

After defining the search keywords, we need to determine the data source to continue. We chose Web of Science and Scopus since they are the most used academic databases with high credibility (Meho and Yang, 2007). In the Web of Science, each keyword pair is used to search for the ”topics” (i.e., titles, abstracts, author keywords, and Keywords Plus.). In Scopus, each keyword pair is used to search for articles whose titles, abstracts, or keywords match. The Web of Science search returned 1089 records. Figure 1 shows the number of results each pair of keywords returned. After removing the duplication among each keyword pair, 685 records were left. The Scopus returned 3064 records. Figure 2 demonstrates the number of results from each pair of keywords. 1724 records were left after combining and removing the duplication of results from each keyword pair.

Records from Web of Science and Scopus were merged, and the duplications were removed using Endnote, a reference library management software. This resulted with 2120 records left. These records went through manual duplication removal and were shortlisted with filtering criteria shown in Table 1.

Table 1: Filtering Criteria

Inclusion Criteria	I1	The publication is an empirical, technical, or theoretical article.
	I2	The publication covers aspects of identified perspectives and fields of computational co-creativity.
Exclusion Criteria	E1	The publication is a technical manual detailing specific technologies.
	E2	Identified perspectives and fields of computational co-creativity are merely mentioned.
	E3	The publication does not involve a co-creation or interaction relationship.
	E4	The co-creation or interaction in the publication doesn’t involve a machine (e.g., the co-creation only happens between human agents in marketing, tourism or public policy).

For filtering, each of the authors screened the first 50 records independently and compared the results with each other. This ensured that all authors shared a mutually agreed understanding of the filtering criteria. Then, the remained records were split into equal parts, and each author filtered their part. The filtering resulted in 1009 records, 916 of them with full-text PDFs available. These 916 full-text articles were used for the analysis described below.

Data Analysis

This systematic literature review includes bibliometric analysis and topic modelling to process the collected data. Details of each analysis are explained below.

Bibliometric Analysis A bibliometric analysis involves analyzing bibliometric data of publications (e.g., citations, titles, and abstracts) quantitatively (Broadus, 1987). The purpose is to mine out the hidden information in academic publications in a specific field (Linnenluecke, Marrone, and Singh, 2020). In recent years, bibliometric analysis has gained popularity thanks to bibliometric software and scientific databases (Donthu et al., 2021). The Bibliometrix package supported by R Programming Language is suggested (Aria and Cuccurullo, 2017; Team, 2013) and it is applied in various studies successfully (Lajeunesse, 2016; Liu, 2022). Bibliometrix supports *.bib* files exported from both Web of Science and Scopus, making it suitable for this study.

We will report bibliometric metrics (i.e., annual scientific production, citation per year, trend topics, and concept co-occurrence network). Annual scientific production and citation per year reveal how related publications and citations appeared each year. Trend topics are expressions frequently appearing in the abstracts of the shortlisted articles. By acknowledging the frequency distribution of each expression, the frequently mentioned historical topics and when they mostly appeared will emerge. Each expression as an analysis unit can be made of one single word (called *unigram*), two consecutive words (called *bigram*), three consecutive words (called *trigram*) and so on. Considering popular expressions of computational co-creativity (e.g., "machine learning") is made up of two words, the abstracts of papers are broken down and each unit is a bigram. A co-occurrence relationship occurs when two units appear together in an abstract. This way, abstracts from articles can be retrieved to identify relationships between units. Units and relationships are visualized as a "co-occurrence network." Each unit is a "node," and each relationship is an "edge." The size of the node corresponds to its frequency of co-occurrence. We can find the most discussed concepts in the previous literature and their relationships using the co-occurrence network analysis. Similar to trend topics, the concept co-occurrence network is generated based on the abstracts of shortlisted papers using bigrams as units. To balance the simplicity and the grasp of the most characteristic part of the co-occurrence network, only the top 20 nodes are reported. Trend topics and the concept co-occurrence network will show how the focus of researchers in the computational co-creativity field and how it has shifted over time.

The results of the bibliometric analysis provide primary insights into academic research on computational co-creativity, but the analysis leaves out the specific content in researches. Because of a large number of articles in the corpus, manual analysis methods such as thematic analysis would have been too cumbersome (Braun and Clarke, 2012). Therefore, a topic modelling approach is incorporated to make this overview study more comprehensive.

Topic Modeling Using Latent Dirichlet Allocation(LDA) Topic modelling is a statistical tool for extracting otherwise hidden structures, and topics from large datasets and is particularly well suited for use with text data (Vayansky and Kumar, 2020). A "topic" is a recurring word pattern that frequently appears together. The topic modelling approach sees every document as a combination of various latent topics with different probabilities (Steyvers and Griffiths, 2007). Through statistical techniques, it is possible to uncover these hidden topics by analyzing the documents to reveal what topics each document embodies and with what probabilities (Barde and Bainwad, 2017). Since we aim to provide a comprehensive positioning of the existing academic publications on computational co-creativity, topic modelling on the full text of these publications can provide helpful insights.

Among several methods for topic modelling, we use "Latent Dirichlet Allocation" (LDA) as applied in natural language processing by Blei, Ng, and Jordan (2003). LDA regards documents as generated from randomized mixtures of hidden topics, seen as probability distributions over words. Such generation is assumed to be based on a Dirichlet prior distribution (Vayansky and Kumar, 2020). LDA is one of the earliest and more frequently utilized topic modelling methods. It is a reliable approach and has been successfully used in studies across various fields (e.g., social media, finance, and university teacher assessment) (Aziz et al., 2022; Buenaño-Fernandez et al., 2020; Geva, Oestreicher-Singer, and Saar-Tsechansky, 2019). Therefore, we use LDA topic modelling to analyze the full text of screened articles, revealing the hidden topics of computational co-creativity studies. The Text Analytics Toolbox of MATLAB is utilized to conduct the LDA topic modelling.

A workflow of LDA modelling includes the following phases: First, collect and import the raw data expected to investigate. Second, clean the data through preprocessing (e.g., tokenize the text, lemmatize the words, remove punctuation, infrequent words, and remove stopwords). Third, build the bag of words based on the cleaned data. That means breaking down the whole article or paragraphs into smaller units for text. One can build the bag of words based on one single unit or combined units. Fourth, build LDA models. LDA modelling requires both the bag of words and *a priori* selected number of topics as inputs. Fifth, choose the model(s) with the most suitable number of topics for more thorough interpretation and reporting.

In our case, the raw data is the full text of all the 916 articles shortlisted. Five bags of words include three separate ones (i.e., unigram, bigram and trigram). It is because these three separate types of bags of words may cover most terms in computational co-creativity (e.g., "creativity", "machine learning", "generative adversarial network"). In addition to these three separate bag of words, we build two combined ones. One is *uni-bigram*, the combination of unigram and bigram. The other is *uni-bi-trigram*, the combination of unigram, bigram, and trigram. These combined bags of words should be more meaningful representations of the published articles (Kaur, Ghorpade, and Mane, 2017). Combined bags of words are also recommended by some popular LDA modelling packages (e.g., the python package "Gensim" which has been used in more than two thousand research papers and student theses (Řehůřek and Sojka, 2010)). Following the best practice (Yue, Wang, and Hui, 2019), eight topic numbers [5, 10, 15, ..., 40] are attempted. These topic numbers may seem arbitrary, but this choice avoids too general emerging topics and allows reasonable manual screening of emerging topics across the models. Therefore, $5 * 8 = 40$ models are built. Each model produces the following outputs: 1) The top 10 highest probability words of each topic and visualized as the word cloud; 2) The top 10 papers that have the highest probability in each topic (i.e., "representative papers of each topic"); 3) Papers where one topic probability is the greater than any other topics' probability; 4) The probability of all topics in the whole dataset; 5) The mixture of all topics' probability in each paper. All the authors went through, discussed and reflected on all of these outputs. We choose models with the most meaningful and interpretable topics for further analysis. Major results of them are reported in the Findings section. The workflow of our LDA modelling is summarized and visualized in Figure 3. Figure 4 below summarizes the workflow of the whole research design.

Findings

Bibliometric Analysis

Figure 5 and Figure 6 show annual scientific production and average citation-per-year for computational co-creativity. Articles were few before the early 2000s, but surged in 2009 and have increased each year since. In 2021 and 2022, 129

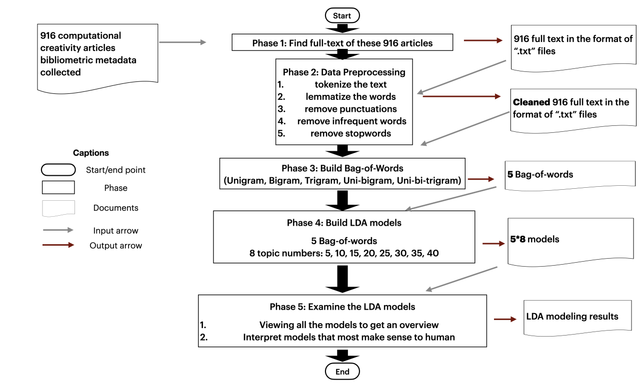


Figure 3: Workflow of LDA modeling

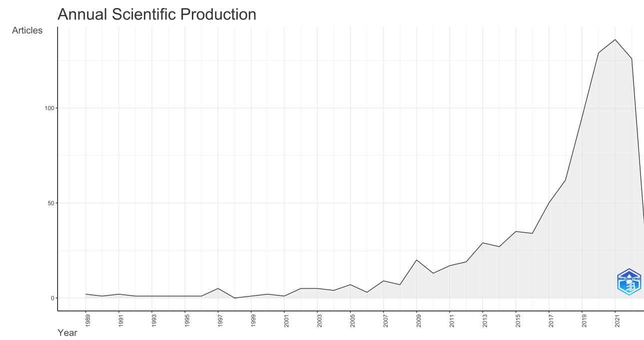


Figure 5: Visualization of Annual Scientific Production

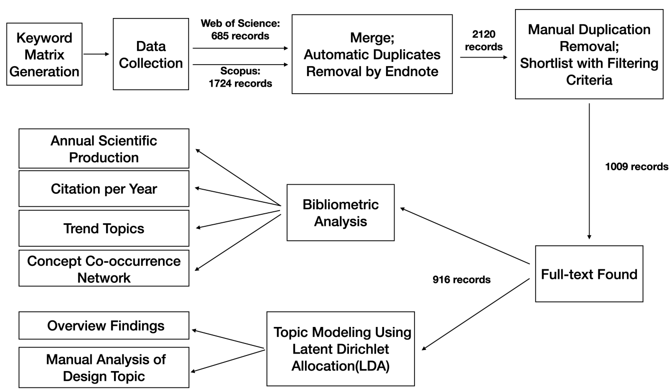


Figure 4: Workflow of Research Design

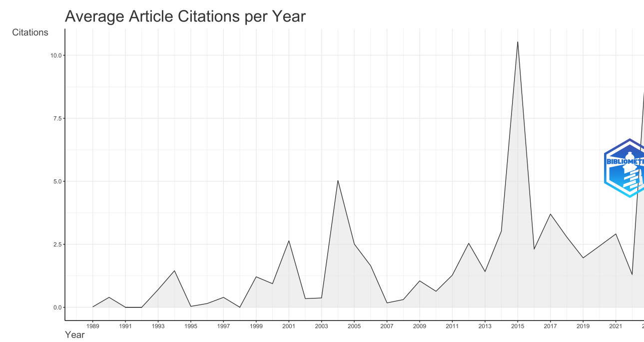


Figure 6: Visualization of Citation per Year (MeanTCperYear)

and 136 annual publications were recorded. The release of GPT-3 in 2021 may have encouraged research in computer-generated content and computational co-creativity. Before 2011, only one paper on computational co-creativity was cited each year on average, but afterwards, more was cited every year. The year 2015 saw high citation numbers, possibly due to the introduction of GAN (Goodfellow et al., 2014) and a paper from Google discussing a neural image caption generator (Vinyals et al., 2015). The increase in publication and citation of articles on computational co-creativity indicates growing interest in the field.

The top 10 trend topics are visualized in Figure 7. The most frequently appeared topic is "artificial intelligence", the enabling approach of much of computational co-creativity. Following it lies "machine learning", one specific method to instantiate AI (Kühl et al., 2020). The following topics, "generative adversarial", "deep learning", "adversarial networks", "neural networks" and "generative models," can be put into one category, namely generative adversarial networks (GANs).These topics are relatively new, as they reached their one-quarter frequency of appearance in 2019.

Topics left belong to a group that emphasizes the role of creativity, such as "computational creativity," "human-computer interaction", and "human creativity". In contrast to GAN-related topics, these terms have fewer appearances and reach their one-quarter frequency earlier.

The concept co-occurrence network is visualized in Figure 8. The concept network is almost totally dominated by the cluster of technology, featuring "artificial intelligence", "machine learning," and "generative adversarial." Many nodes belong to this technology, most frequently appearing in the papers' abstracts. On top of that, there are diversified and frequent co-occurrence relationships among these nodes. Therefore, the cluster of computational co-creativity technology concepts has formed a complex and robust network. In contrast, there is only one different cluster in the whole network: "human creativity" and "computational creativity." This cluster of creativity has much fewer nodes and edges. Each node has fewer frequency of co-occurrence. This cluster of creativity is a simple and fragile network.

To sum up, the bibliometric analysis demonstrates that computational co-creativity has become a popular research field in recent years and decades. Not only are people interested in doing research about it, but people also like reading and citing these papers. However, **the current research on computational co-creativity is heavily technology-oriented, specifically focusing on the generative adversarial networks.** "Creativity" does have a place, but it's almost dominated by technology. These are the primary findings from the bibliometric analysis of the abstracts of papers.

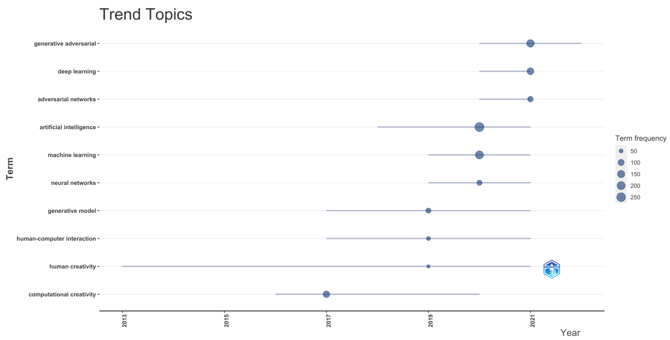


Figure 7: Top 10 Trend Topics

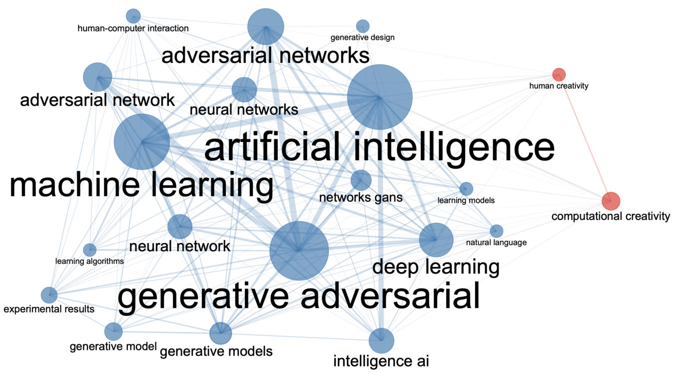


Figure 8: Concept Co-occurrence network.

Topic Modeling Using Latent Dirichlet Allocation(LDA)

Overview Findings As mentioned earlier, 40 LDA models are trained in this study, covering 5 bags of words and 8 topic numbers. Due to space limitations, we will elaborate on only three representative models based on the bag of words of combined unigrams and bigrams. Readers are welcome to contact the authors if interested in all the results. These three models are selected as a tradeoff between specificity and interpretability compared to other models. They are the "Uni-bigram, 10 Topics" model (Model A), the "Uni-bigram, 15 Topics" model (Model B), and the "Uni-bigram, 20 Topics" model (Model C). The overview of the three models is presented in the word cloud figures in Figure 9. In all three models, "technology" (and a related term "technique") has appeared in the topic to which most papers belong. It appeared in four topics among the three models. Considering the enabling role of technology in computational co-creativity, it is totally understandable. However, the most frequent appearance of "technology" strongly indicates that the current research in computational co-creativity is highly technology-oriented. Another thing is "design" (and "designer") also appeared in three models. Among the three models, "design" has appeared in four topics. This indicates that "design" emerges as an important theme in computational co-creativity literature. Nevertheless, "design" is highly related to terms "tool" (Topic 8 of Model A; Topic 13 of Model B; Topic 16 of Model C) and "system" (Topic 5 of Model B; Topic 16 of Model C). Therefore, the design mentioned in previous computational literature is probably from a mainly instrumental perspective. In order to clarify his issue, we do a further analysis of papers related to design topic in the investigated LDA models.

We also perform a more thorough interpretation of one of the three models. This topic interpretation entails going through the topic representations of the model, i.e., top keywords and their probabilities, word cloud visualization, top representative papers, overall topic probability distribution, and visualization of topic distributions of individual papers. This helps to specify the 'core' meaning of the topic. Next, the topic is given a short description and references to two most representative papers on the topic. The results for one of the models (the "Uni-bigram, 15 Topics" model (Model B)) are shown in Table 2 below. This one is chosen because 15 is an appropriate number of topics, again, balancing specificity and interpretability. Also, among all the 40 models we train, Model B results made most sense to the authors.

Manual Analysis of Design Topic Although not adequately embodied in the abstract of papers, the design emerges as an important topic in all three uni-bigram LDA models built on the full text of computational co-creativity papers. In fact, design as a topic was present in all the 40 models we investigate. Further manual analysis of titles and abstracts of papers with "design" as their main topic (100 papers) revealed that they fall into five categories: design and/or evaluation of a specific computational co-creativity application, e.g., (Kantosalo and Riihiaho, 2019; Calderwood et al., 2020); reviews of existing research and systems e.g. (Mountstephens and Teo, 2020; Kapur and Ansari, 2022); design support tools e.g., (Nakakoji, Yamamoto, and Ohira, 2000; Bonnardel and Marmèche, 2005); general creativity research, e.g., (Edmonds et al., 2005; Algarni, 2020), and three papers related to *speculative* or *critical design* (Bardzell, Bardzell, and Koefoed Hansen, 2015; Reddy, 2022; Liikkanen, 2019).

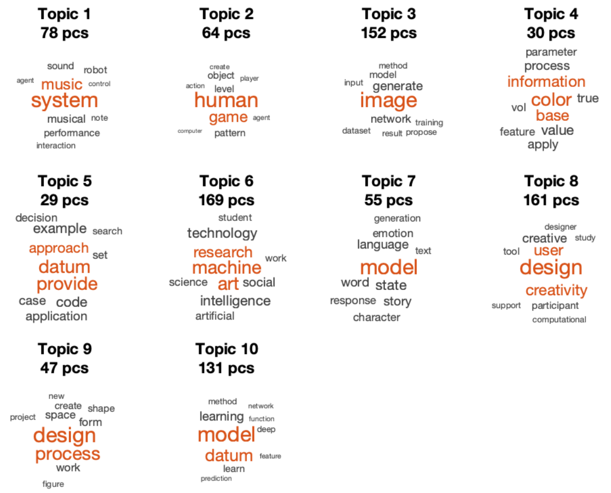
Among the three papers related to critical or speculative design, (Liikkanen, 2019) is a short paper not discussing critical or speculative design per se but rather encouraging HCI researchers to pay more attention to how generative AI will challenge and change the interaction design profession. (Reddy, 2022) outlines a 'critical making' practice in exploring AI and human collaborative creativity. (Bardzell, Bardzell, and Koefoed Hansen, 2015) is a generic call for engaging with more critical ways of creating knowledge within research through design HCI research. In summary, although these three papers are related to speculative and critical design, only (Reddy, 2022) specifically focuses on computational co-creativity. This seems to indicate that these approaches are underrepresented in the research field.

We conduct additional Scopus and Web of Science (WoS) inquiries to investigate this argument further. Searching keywords are used to screen articles whose title, abstract or keyword match. Table 3 shows the result.

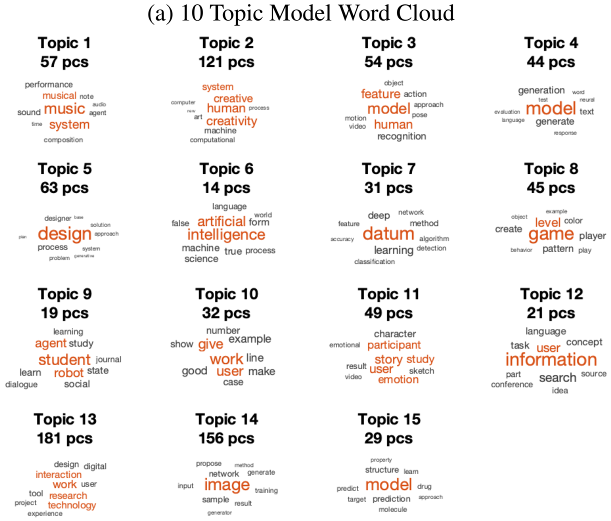
In addition to (Reddy, 2022) and (Liikkanen, 2019) mentioned above, (Brassett, 2016) discusses design and specu-

Table 2: Topic Interpretation and Representative Papers in Model B

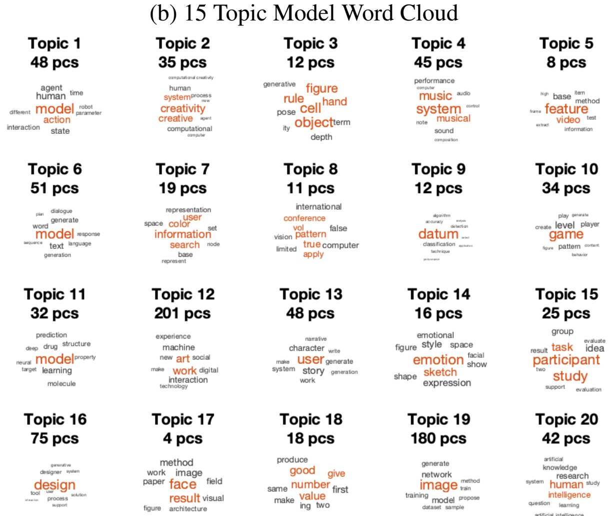
Topic No.	Interpretation	Representative Papers
1	music composition and performance	1) Ting, C.-K.; Wu, C.-L.; and Liu, C.-H. 2015. A novel automatic composition system using evolutionary algorithm and phrase imitation. IEEE Systems Journal 11(3):1284–1295. 2) Kirke, A., and Miranda, E. R. 2009. A survey of computer systems for expressive music performance. ACM Computing Surveys (CSUR) 42(1):1–41
2	overall aspects of computational co-creativity	1) Coeckelbergh, M. 2017. Can machines create art? Philosophy & Technology 30(3):285–303. 2) Kirke, A., and Miranda, E. R. 2009. A survey of computer systems for expressive music performance. ACM Computing Surveys (CSUR) 42(1):1–41
3	object, action, and human recognition	1) Zhang, S.; Wei, Z.; Nie, J.; Huang, L.; Wang, S.; Li, Z.; et al. 2017. A review on human activity recognition using vision-based method. Journal of healthcare engineering 2017. 2) Li, X.; Liu, S.; Kim, K.; Wang, X.; Yang, M.-H.; and Kautz, J. 2019. Putting humans in a scene: Learning affordance in 3d indoor environments. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 12368–12376.
4	language and dialogue generation	1) Lee, P.; Fyffe, S.; Son, M.; Jia, Z.; and Yao, Z. 2022. A paradigm shift from human writing" to "machine generation" in personality test development: an application of state-of-the-art natural language processing. Journal of Business and Psychology 1–28. 2) Belainine, B.; Sadat, F.; and Boukadoum, M. 2022. End-to-end dialogue generation using a single encoder and a decoder cascade with a multidimension attention mechanism.IEEE Transactions on Neural Networks and Learning Systems.
5	design and design processes	1) Dilibal, S.; Nohut, S.; Kurtoglu, C.; and Owusu-Danquah, J. 2021. Data-driven generative design integrated with hybrid additive subtractive manufacturing (hasm) for smart cities. In Data-Driven Mining, Learning and Analytics for Secured Smart Cities: Trends and Advances. Springer. 205–228. Mountstephens, 2) J., and Teo, J. 2020. Progress and challenges in generative product design: A review of systems. Computers 9(4):80.
6	general artificial intelligence in creativity	1) Cerrito, C. D. 2010. Creating with cobots. In Proceedings of the fourth international conference on Tangible, embedded, and embodied interaction, 395–396. 2) de Silva Garza, A. G., and Gero, J. S. 2010. Elementary social interactions and their effects on creativity: A computational simulation. In ICCC, 110–119.
7	algorithms, architectures, and techniques	1) Habuza, T.; Navaz, A. N.; Hashim, F.; Alnajjar, F.; Zaki, N.; Serhani, M. A.; and Statsenko, Y. 2021. Ai applications in robotics, diagnostic image analysis and precision medicine: Current limitations, future trends, guidelines on cad systems. 2) Chale, M., and Bastian, N. D. 2022. Generating realistic cyber data for training and evaluating machine learning classifiers for network intrusion detection systems. Expert Systems with Applications 207:117936.
8	procedural content generation and behavioural models in games	1) Cutumisu, M.; Szafron, D.; Schaeffer, J.; Waugh, K.; Onuczko, C.; Siegel, J.; and Schumacher, A. 2006. A demonstration of scriptease ambient and pc-interactive behavior generation for computer role-playing games. In Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, volume 2, 141–142. 2) Kumaran, V.; Mott, B.; and Lester, J. 2019. Generating game levels for multiple distinct games with a common latent space. In Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, volume 15, 102–108.
9	human-machine relationships in co-creativity	1) Griffith, A. E.; Katuka, G. A.; Wiggins, J. B.; Boyer, K. E.; Freeman, J.; Magerko, B.; and McKlin, T. 2022. Investigating the relationship between dialogue states and partner satisfaction during co-creative learning tasks. International Journal of Artificial Intelligence in Education 1–40. 2) Sundararajan, L. 2014. Mind, machine, and creativity: an artist's perspective. The Journal of creative behavior 48(2):136–151.
10	computational support for specific creative tasks	1) Watanabe, K.; Matsubayashi, Y.; Inui, K.; Nakano, T.; Fukayama, S.; and Goto, M. 2017. Lyrisys: An interactive support system for writing lyrics based on topic transition. In Proceedings of the 22nd international conference on intelligent user interfaces, 559–56. 2) Williams, H., and McOwan, P. W. 2014. Magic in the machine: a computational magician's assistant. Frontiers in psychology 5:1283.
11	interactive storytelling and co-creation	1) Bacher, J. T., and Martens, C. 2021. Interactive fiction creation in villanelle: Understanding and supporting the author experience. In 2021 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC), 1–5. IEEE. 2) Rico Garcia, O. D.; Fernandez Fernandez, J.; Becerra Saldana, R. A.; and Witkowski, O. 2022. Emotion-driven interactive storytelling: Let me tell you how to feel. In Artificial Intelligence in Music, Sound, Art and Design: 11th International Conference, EvoMUSART 2022, Held as Part of EvoStar 2022, Madrid, Spain, April 20–22, 2022, Proceedings, 259–274. Springer.
12	human perceptual and cognitive capabilities in computational co-creativity	1) Algarni, A. 2020. Neuroscience of creativity in human computer interaction. In Proceedings of the Future Technologies Conference (FTC) 2019: Volume 1, 248–262. Springer. 2) Bonnardel, N., and Marm'eche, E. 2005. Towards supporting evocation processes in creative design: A cognitive approach. International journal of human-computer studies 63(4-5):422–435.
13	creative processes in interaction design	1) Lee, Y.-C., and Llach, D. C. 2020. Hybrid embroidery: exploring interactive fabrication in handcrafts. In ACM SIG-GRAPH 2020 Art Gallery. 429–433. 2) Ryskeldiev, B.; Ili c, S.; Ochiai, Y.; Elliott, L.; Nikonole, H.; and Billinghurst, M. 2021. Creative immersive ai: Emerging challenges and opportunities forcreative applications of ai in immersive media. In Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, 1–3.
14	adversarial networks for visual and spatial tasks	1) Han, X.; Yang, H.; Xing, G.; and Liu, Y. 2019. Asymmetric joint gans for normalizing face illumination from a single image. IEEE Transactions on Multimedia 22(6):1619–1633. 2) Pang, Y.; Xie, J.; and Li, X. 2018. Visual haze removal by a unified generative adversarial network. IEEE Transactions on Circuits and Systems for Video Technology 29(11):3211–3221.
15	artificial intelligence and machine learning in drug discovery	1) Choudhury, C.; Murugan, N. A.; and Priyakumar, U. D. 2022. Structure-based drug repurposing: Traditional and advanced ai/ml-aided methods. Drug Discovery Today. 2) Bilodeau, C.; Jin, W.; Jaakkola, T.; Barzilay, R.; and Jensen, K. F. 2022. Generative models for molecular discovery: Recent advances and challenges. Wiley Interdisciplinary Reviews: Computational Molecular Science 12(5):e1608.



(a) 10 Topic Model Word Cloud



(b) 15 Topic Model Word Cloud



(c) 20 Topic Model Word Cloud

Figure 9: Word Cloud Figure of Three Uni-bigram LDA Models

Table 3: Inquiry of Critical Design and Speculative Design in Computational Co-creativity publications

Search Keywords	Source	Number of Results	Related Articles
computational AND creativity AND speculative AND design	Scopus	5	(Brassett, 2016)
	WoS	5	(Brassett, 2016)
computational AND creativity AND critical AND design	Scopus	60	(Reddy, 2022)
	WoS	55	(Reddy, 2022)
generative AND ai AND speculative AND design	Scopus	4	(Wood, 2021)
	WoS	3	N/A
generative AND ai AND critical AND design	Scopus	19	(Wood, 2021; Reddy, 2022; Liikkanen, 2019)
	WoS	37	(Reddy, 2022; Liikkanen, 2019)

lation through a philosophical approach, incorporating interpretations of Simondon, Deleuze, Guattari, and Spinoza. (Wood, 2021) describes 'poetic methods' as an approach inspired by speculative and critical design. Poetic methods include installation, encounters, and performances developed in a participatory manner with public engagement. This opens up ways for more discursive, open-ended, and future-oriented ways of understanding how technologies affect our lives.

As Web of Science and Scopus do not necessarily have a wide enough cover, we also conduct a brief Google Scholar Search with the same keywords. Even this search returned only a handful of relevant publications, all recent (Ullstein and Hohendanner, 2020; Buschek et al., 2021; Houde et al., 2020; Jang and Nam, 2022; Muller et al., 2022).

The results of bibliometric analyses, LDA modelling, and further manual literature review show that the current computational co-creativity research is heavily technology-oriented, specifically leaning on the generative adversarial network approach. In contrast, the role of design in the papers either focuses on applications of certain technologies or overlooks other design elements.

Discussion

Based on the bibliometric analysis and LDA modelling results, we can respond to the two research questions proposed in the introduction section:

- **What are the well-defined research directions in terms of human-computer co-creativity?** Current research directions of human-computer co-creativity mostly fall in the category of technology, especially generative adversarial networks and other broader directions (e.g., deep learning, neural network, machine learning, and artificial intelligence).

- **Specifically, what's the role of *design* in current research?** There are four points: 1) Design indeed appeared in multiple topics, so it's not absent; 2) Compared with technology, design takes much less portion in the existing computational co-creativity research; 3) The current discussion of design is also highly technology-oriented; 4) Speculative and critical design approaches are rare in computational co-creativity and generative AI.

Current technology-focused research on computational co-creativity is based on implicit value, motivation and orientation in their given designs. At the same time, a lack of critical reflection and alternative future exploration in computational co-creativity and generative AI is embodied by the insufficient discussion on the design itself. Such a lack may narrow our horizons and shrink the possibility of spaces where computational co-creativity could have been. In this way, such a lack will prevent us from a comprehensive understanding of computational co-creativity and generative AI, which will endanger this field's long-term development.

We propose **research through speculative and critical interaction design** as a worthwhile approach to pursue further. In research through design (RtD), actual artifacts are designed and made to respond to specific research questions (see, e.g., (Zimmerman, Forlizzi, and Evenson, 2007)). Speculative design (Auger, 2013; Wong and Khovanskaya, 2018) aims at imagining alternative futures and how the designed objects would alter, shape, and redefine our human world. Speculative design projects look beyond what is technologically or culturally possible right now and can thus contribute to the trajectories of technology development. Critical design, on the other hand, aims to challenge our assumptions of how these designed objects would fit in our human world (Dunne and Raby, 2013; Bardzell et al., 2012). Critical design provokes and critiques rather than provides solutions. Thus, research through speculative and critical design allows us to imagine different futures, which helps us to prepare for them. This approach aims at widening our understanding of what would matter and to whom in our future worlds, especially from diversity, equity, and inclusion points of view. It will also help us reveal the underlying ideologies and ecosystems of current and near-future approaches in computational co-creativity and generative AI. The astonishing speed at which these technologies are developing requires such future-oriented design approaches to anticipate and shape how they will affect our world. There could be alternative ways to achieve such a critique and reflection on computational creativity. For example, critical analysis and creative writing may also contribute knowledge in this area. The perspective of research through design, speculative design and critical design is only one possible approach. Nevertheless, considering the interactive essence of computational co-creativity tools, a design-based approach may be more appropriate for the **direct** experience, knowledge and reflection from users and developers.

Besides this research, there are also other ways to develop speculative and critical design perspectives in computational co-creativity. First, **co-speculation Workshops.** To place end-users of design in focus, we plan to carry out co-speculation workshops with post-workshop interviews or focus groups. Co-speculation is a collaborative method within speculative design practices that incorporates non-design experts (Desjardins et al., 2019; Wakkary et al., 2018). Second, **co-speculating with sketches and prototypes.** We plan to use design sketches, user experience scenarios, and low-fidelity prototypes as conversation prompts in a series of co-speculative workshops. Sketching is a fundamental part of the design process that helps designers generate and discuss design ideas (Greenberg et al., 2012). The design process is more about getting the right design, than getting one design right. To get the right design, one should consider many ideas rather than a single one to find a better overall solution (Buxton, 2007). To achieve this we will: 1) generate as many ideas as possible, e.g., inspired by brainstorming, discussions, lateral thinking, client discussions, observations of end users, etc.; 2) choose the most promising ones after reflecting on all the ideas and then develop them further parallelly; 3) add new ideas when they come up during further design work.

Limitations

In this paper, we determine suitable topic numbers for further evaluation by exhausting as many modeling settings as possible and then manually screening them. There are, however, ways to automatically evaluate the models. For example, the R package "ladtuning" can synthesize multiple methods of evaluating the most suitable topic number and present the result automatically (Nikita, 2016; Geva, Oestreicher-Singer, and Saar-Tsechansky, 2019). Using these packages would improve the validity and credibility of methods used in LDA modeling. However, even with these automatic evaluations, interpretations from researchers are still indispensable.

The other limitation is the data collected. We only bring the abstracts and full text from Web of Science and Scopus into consideration. computational co-creativity must have publications beyond these databases as an emerging and active field. Future studies can involve more data from different sources for a more comprehensive scoping.

Conclusion

This position paper reports results from a bibliometric analysis and Latent Dirichlet allocation (LDA) topic modelling on 916 research articles on human-computer interaction and computational creativity. The analyses revealed that the field is dominated by technology-oriented research and that although design emerged as a topic, it was heavily oriented towards instrumental perspectives. Additional analysis of design-related papers identified a lack of critical speculation on the potential impact of the widespread adoption of computational creativity. Therefore, we would like to call for critical and speculative design perspectives to examine these human-computer co-creation relationships and propose alternative value orientations and approaches for further research and development of computational creativity.

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