How to use Generative AI as a design material for future human-computer (co-)creation?

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The recent boom of computational technologies (e.g., artificial intelligence (AI) and machine learning (ML)) has demonstrated their potential to impact human-computer interaction (HCI) by creating a new co-creation relationship, human-computer co-creativity. This human-computer co-creativity relationship can affect the current approaches to the production-consumption and producers-consumers of HCI products. This study provides a systematic literature overview of computational co-creativity research. Articles from Scopus and Web of Science databases are pulled and shortlisted into 916 articles. Bibliometric analysis of their abstracts and a Latent Dirichlet Allocation (LDA) topic modeling on their full text is 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 primarily focuses on technology while design, especially speculative and critical design, is underrepresented. Accordingly, this paper calls for more design-oriented research to develop a more comprehensive understanding of human-computer co-creativity, especially from critical and speculative design perspectives.

Additional Key Words and Phrases: generative artificial intelligence, human-computer co-creativity, speculative design, critical design

1 INTRODUCTION

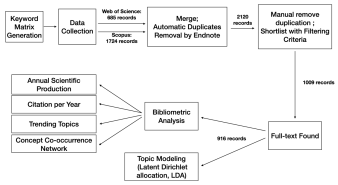
Artificial intelligence (AI) and machine learning (ML) technologies have been part of human-computer interaction research for a long time. Although AI and ML have been frequently used in productivity fields (e.g., auto driving), they have recently demonstrated their capability in co-creativity thanks to the iteratively optimized algorithms. This evolution gives rise to the current massive interest in Generative AI (GenAI). For example, large-scale language models such as ChatGPT 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 on their assignments, which seemed to threaten academic honesty [24]. Meanwhile, text-to-image systems, such as Dall-E 2, Midjourney, and Stable Diffusion, have garnered support from millions of users exploring the opportunities, limitations, and challenges of automatically created images that are virtually indistinguishable from ones created by humans. The adoption of these generative AI technologies into other creative activities (e.g., full-length movie creation) seems unstoppable.

Current applications of computational creativity (i.e., text and graphic illustrations) are mainly for non-interactive media. However, considering the recent advancement in generative AI and other computational technologies in the creativity field, it is high time for the academic community to have a reflective overview of the essential human-computer co-creativity relationship. Therefore, this proposal investigates the existing human-computer (co-)creativity academic research with the following more specific 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?
- What could be fruitful future agendas for human-computer co-creativity research?

2 LITERATURE REVIEW WITH BIBLIOMETRIC ANALYSIS AND TOPIC MODELING

This study conducts a systematic literature review to seek answers to the research questions. We perform a bibliometric analysis and Latent Dirichlet allocation (LDA) topic modeling with total 916 papers pulled from Web of Science and Scopus databases. Search keywords and the number of results returned in each database is displayed in the keyword matrix. They as well as the sequential research workflow as suggested by Kitchenham [20] are shown in Fig 1.



(a) Workflow of Research

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

(b) Keyword Matrix, WoS

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

(c) Keyword Matrix, Scopus

Fig. 1. Research Design

2.1 Research Design

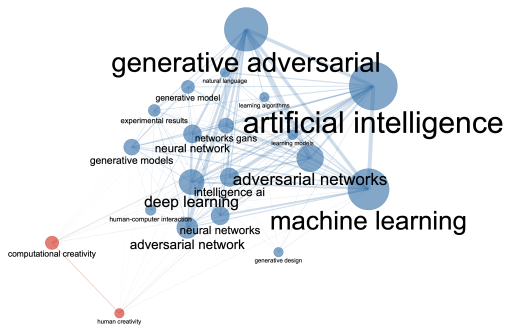
A bibliometric analysis involves analyzing bibliometric data (e.g., citations, titles, and abstracts) quantitatively [10]. The purpose is to find out hidden information, such as the volume of publication and citation and concept co-occurrence networks, of academic publications in a specific field [22]. Although bibliometric analysis help grasp different aspects of academic publications through meta-data, it is inadequate for analyzing the detailed contents of these studies. For example, the trending topics and concept co-occurrence network are analyzed based on only the abstracts of papers instead of full texts. Therefore, topic modeling is conducted to further investigate what the research directions in computational creativity are.

Topic modeling is a statistical tool for extracting variables from large datasets and is particularly well suited for use with text data [7, 29]. It is used for discovering hidden structures from a collection of documents. A "topic" is a recurring pattern of words that frequently appear together in documents. The topic modeling approach sees every document as a combination of various latent topics with different probabilities [23]. Among several methods for topic modeling, this paper uses the "Latent Dirichlet Allocation" (LDA) developed by Blei et al. [8]. LDA is one of the earliest and more frequently utilized topic modeling methods and it has been successfully used in studies across various fields (e.g., social media, finance, and university teacher assessment [4, 11, 16]). This study uses LDA to analyze the full text of the articles.

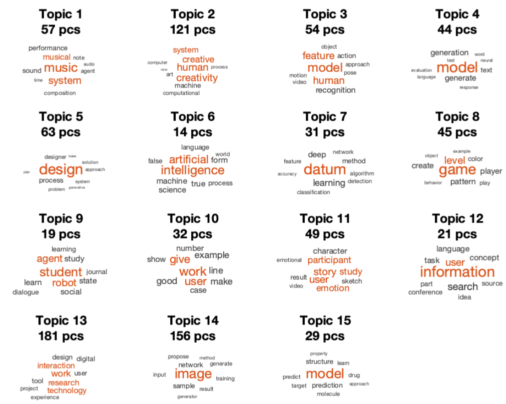
2.2 Primary Findings

2.2.1 Bibliometric Analysis. A co-occurrence relationship occurs when two units appear together in a document, in our case abstracts of academic papers. Units here can be words or sequences of words. In 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" (see Fig 2a). The size of the node corresponds to its frequency of co-occurrence. Topics including *generative adversarial*, *adversarial networks*, and *generative model(s)* belong to one category, generative adversarial network (GAN), which is a specific kind of machine learning algorithm to make the computer generate real-like contents such as photorealistic images [1]. From this perspective, the network is dominated by the cluster of *GAN*, *artificial intelligence*, and *machine learning* nodes. None of them, however, have a strong connection with nodes of *computational creativity* and *human creativity* in the co-occurrence network. Nor do the nodes of *computational creativity* and *human creativity* have big weights in this network.

2.2.2 Topic Modeling using LDA. Topic modeling using LDA needs two a priori parameters. One is the Ngram, namely how many words make up a unit of analysis. Unigram means every one word is a unit, bigram is every two words, and trigram is every three words. The other is the number of topics. Since this proposal is primarily exploratory, we follow



(a) Concept co-occurrence network. To balance the simplicity and the grasp of the most characteristic part of the co-occurrence network, only the top 30 nodes from 6 clusters are reported.



(b) 15 Topic Uni-bigram Word Cloud

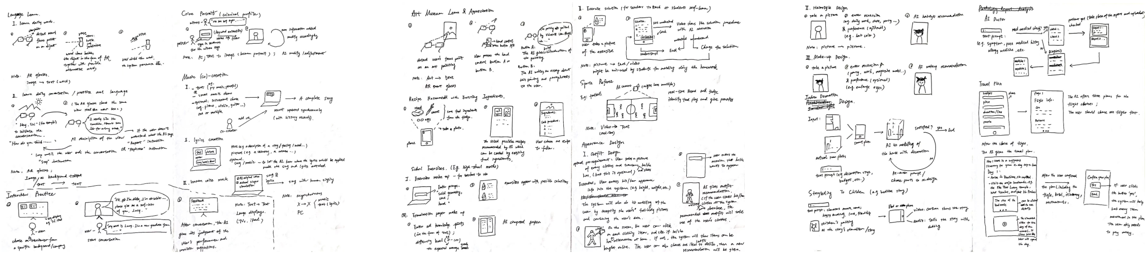
Fig. 2. Results for bibliometric analysis and topic modeling using LDA.

previous practices like [31] by trying various topics number from 5, 10, 15... to 40. We also tried unigram, bigram, and trigram individually. The combinations of unigram-bigram and unigram-bigram-trigram were also experimented with. In total, forty LDA models have been trained. Limited to the length of this paper, we only show the topics of the model "Uni-bigram, 15 Topics" in Fig 2b as an example of models. We find that **"design" appeared in all these forty LDA models built on the full-text of papers**. However, "design" seldom falls into the topic where most papers belong and it almost always co-appears with "tool" and "system." Although design is not absent in the previous discussions of computational creativity, it is still mainly from an instrument perspective. Further manual analysis of titles and abstracts with "design" as their main topic (100 papers) reveal that they fall into five categories: design and/or evaluation of a specific computational co-creativity application [13, 18]; reviews of existing research and systems [19, 25]; design support tools [9, 26]; general creativity research [2, 15], and *speculative* or *critical design* [5, 21, 27]. Among the three papers related to speculative and critical design, only [27] specifically focuses on computational co-creativity. This seems to indicate that these approaches are underrepresented in the research field.

Results of bibliometric analyses and topic modeling indicate the current computational creativity research seems heavily technology-oriented, specifically leaning on the generative adversarial network approach. In contrast, design is scarcely discussed and is heavily rooted in technology or instrument. Speculative and critical design on computational creativity, however, is underrepresented. This may hinder us from a comprehensive understanding of GenAI and other forms of computational creativity which endangers long-term development.

3 HOW TO SPECULATE ON GENAI

The result of our systematic literature review shows that there are literally hundreds of computational creativity projects utilizing functionality that the current GenAI technologies can provide. However, inadequate attention is paid to investigating what the user experiences and interaction architectures of GenAI systems would be like in the future. The challenges these systems will have on economic, political, legal, aesthetic, ethical, and societal issues have remained little explored in a systematic way. Thus, the goal is to foster reflective and critical engagement not just with what and how things are at the present but with what could be developed in the future [28].



(a) Sketch one. (b) Sketch two. (c) Sketch three.

Fig. 3. Sketches for GenAI in various application cases.

Research Through Speculative and Critical Design. The general approach that this study proposes consists of research through speculative and critical design focusing on human-computer (co-)creation. In research through design (RtD), actual artifacts are designed and made in order to respond to specific research questions [32]. Speculative design [3] aims at imagining alternative futures and how the designed objects would alter, shape, and redefine our human world. Critical design, on the other hand, aims to challenge our assumptions of how these designed objects would fit in our human world [6]. Thus, research through speculative and critical design allows us to imagine different futures in concrete ways, which helps us to prepare for them.

Co-speculation Workshops. To place end-users of design in focus, we plan to carry out co-speculation workshops with interviews or focus groups. Co-speculation is a collaborative method within speculative design practices that incorporates non-design experts [14, 30].

Co-speculating with sketches and prototypes. We plan to use design sketches (see Fig 3 for examples of initial 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 [17]. 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 [12]. To achieve this we will:

- generate as many ideas as possible, e.g., inspired by brainstorming, discussions, lateral thinking, client discussions, observations of end users, etc.;
- choose the most promising ones after reflecting on all the ideas and then develop them further parallelly;
- add new ideas when they come up during further design work.

In the future, we are going to develop the most promising sketches into more detailed user experience scenarios and low-fidelity prototypes for further co-speculative workshops. We will use the results to summarize interaction design implications for future GenAI systems.

4 CONCLUSION

By carrying out bibliometric and topic modeling analysis of the literature related to human-computer (co)-creation, this study put forward the urgent need to speculate on the potential of this incredibly fast-evolving GenAI technology, thinking about the future user experiences and interaction architectures of GenAI applications. We propose that research through speculative and critical design (e.g., co-speculation workshops with focus groups) would be a way to help understand how to develop GenAI systems in the next 5 to 10 years.

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