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Proceedings of EKSIG Conference 2025: Data as Experiential Knowledge and Embodied Processes

Mary Karyda

Damla Çay

Ágnes Karolina Bakk

Renáta Dezső

Jessica Hemmings

See next page for additional authors

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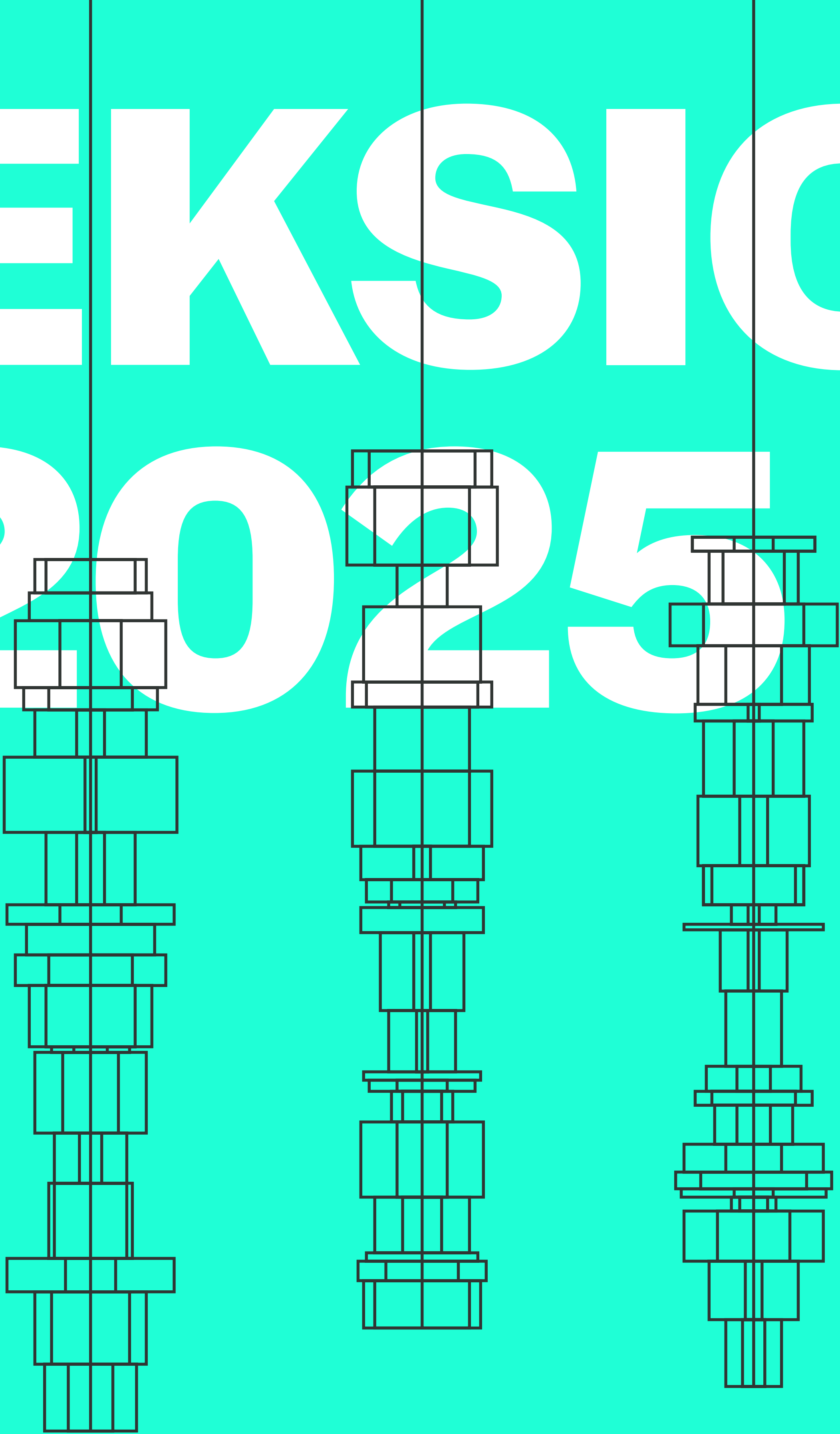
Editors
Mary Karyda, Damla Çay, Ágnes Karolina Bakk, Renáta Dezső, Jessica Hemmings, and Nithikul Nimkulrat

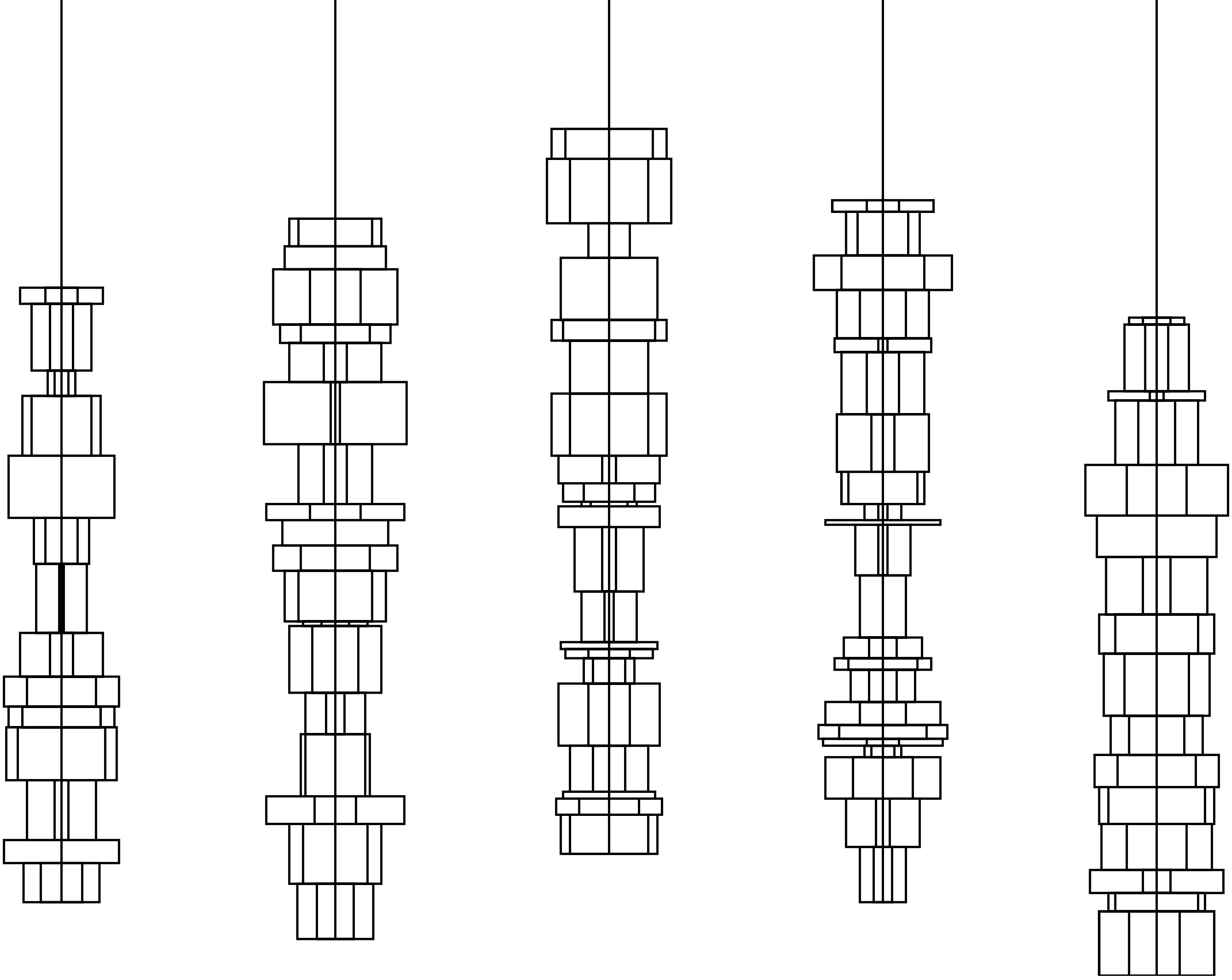
EKSIG 2025



DATA AS EXPERIENTIAL KNOWLEDGE AND EMBODIED PROCESSES

MOHOLY-NAGY UNIVERSITY OF ART AND DESIGN

BUDAPEST 12-13 MAY 2025



Editors:
Mary Karyda, Damla Çay, Ágnes Karolina Bakk,
Renáta Dezső, Jessica Hemmings, Nithikul Nimkulrat

Graphic Design:
Király Bálint (kiraly@mome.hu)

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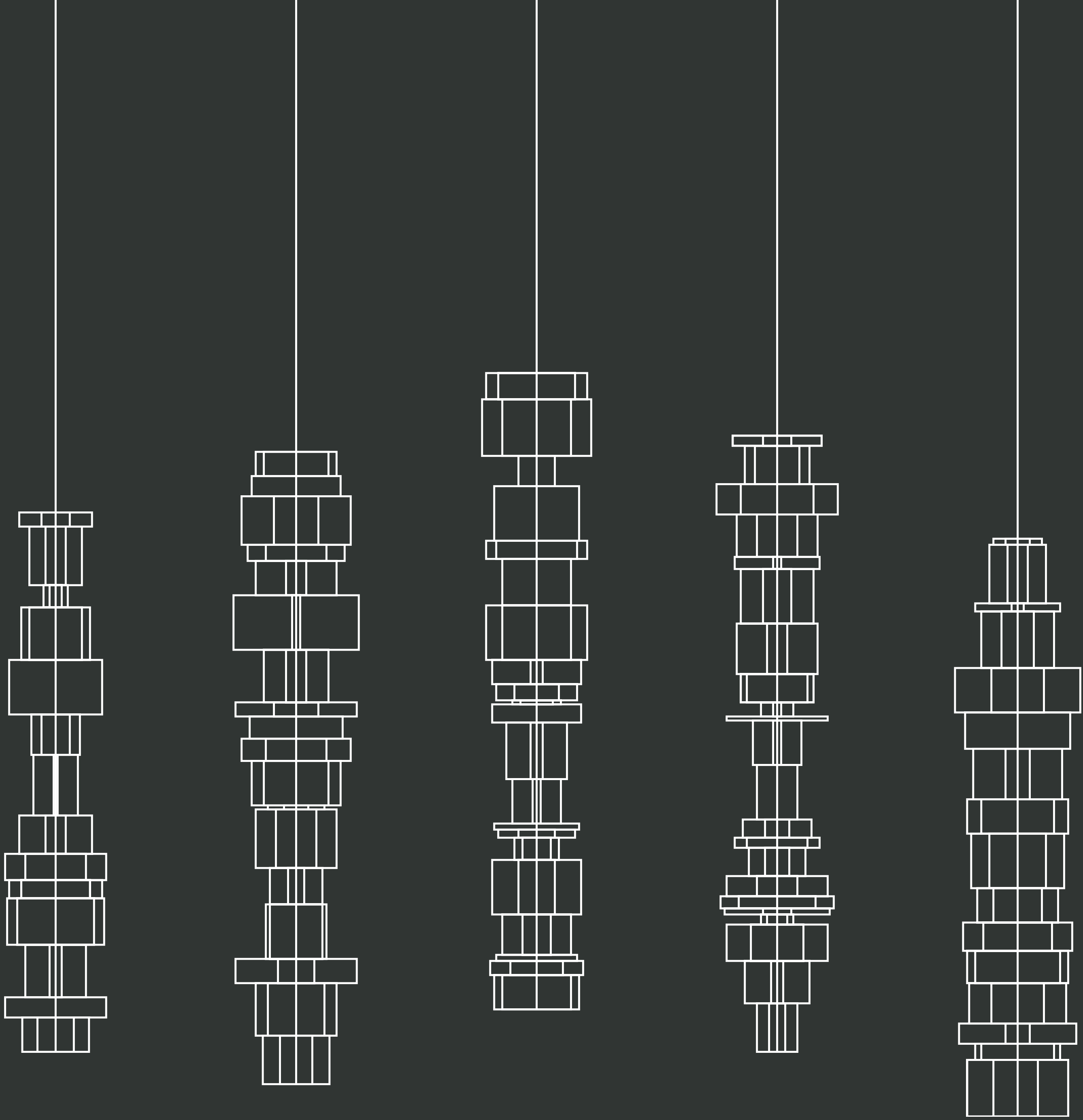

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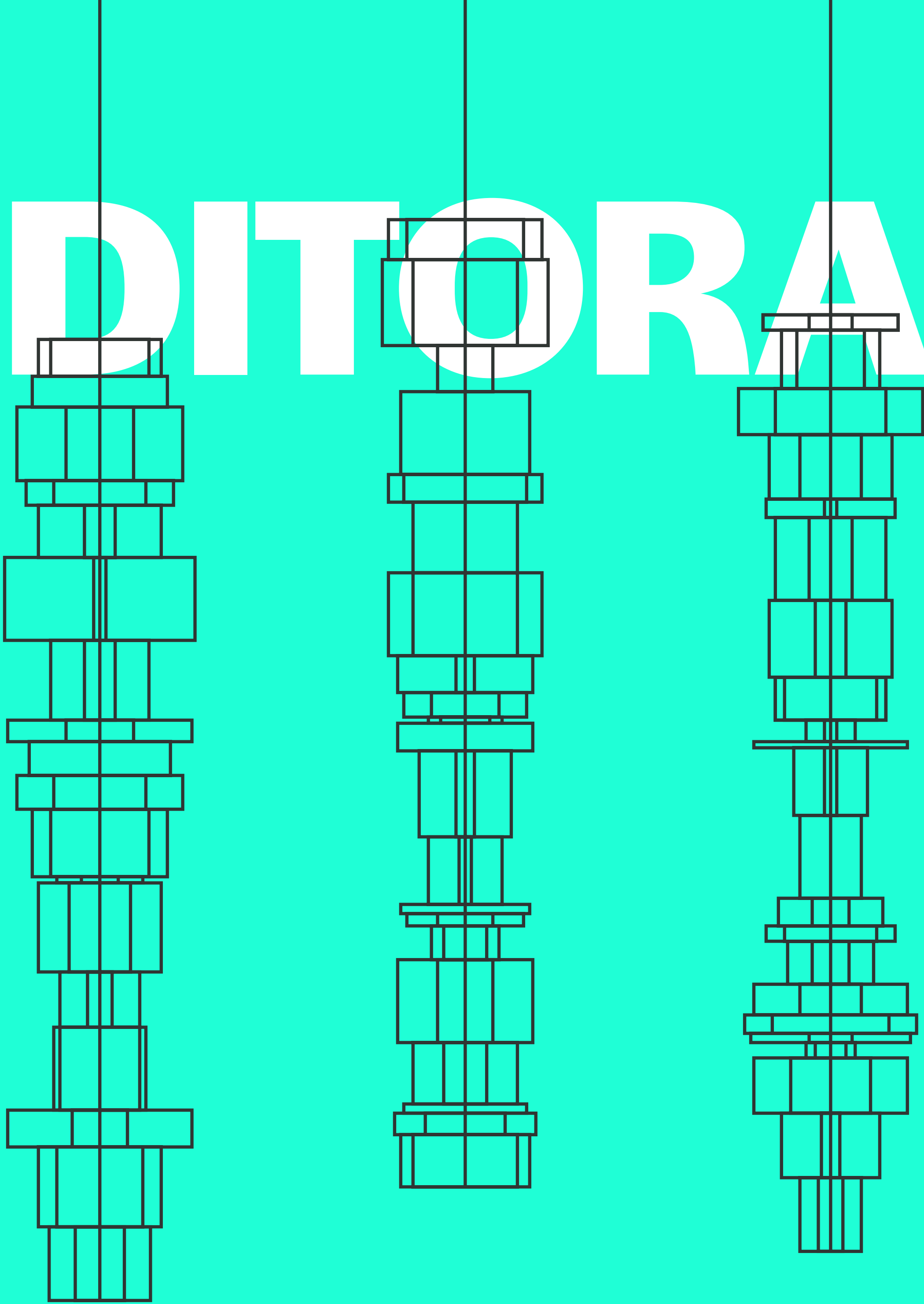
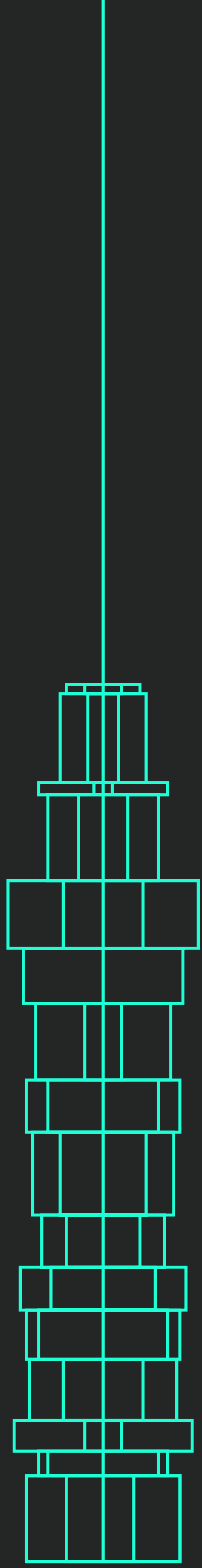
EDITORAL



EDITORAL

EKSIG 2025: Data as Experiential Knowledge and Embodied Processes1, International Conference 2025 of the DRS Special Interest Group on Experiential Knowledge (EKSIG), aimed to provide a forum for debate about knowledge generation in collaboration by professionals and academic researchers in the creative disciplines and beyond. These proceedings contain the keynote speakers' abstracts and the full papers accepted through double blind review for the EKSIG 2025 held on 12thand 13th May 2025 at Moholy-Nagy University of Art and Design.



KEYNOTES SPEAKERS

MIRIAH MEYER

ANDREW VANDE MOERE

MIHÁLY MINKÓ

PAPER INDEX BY TRACK

TRACK 1: DATA IN EDUCATION

TRACK 2: CRAFTING WITH DATA

TRACK 3: DATA IN HEALTH

TRACK 4: DATA IN PROCESSES

TRACK 5: SENSING DATA

TRACK 6: DATA CULTURES

TRACK 7: DATA FUTURES

TRACK 8: TRANSFORMATIVE DATA

CONFERENCE ORGANIZATION

EKSIG 2025 IS ORGANIZED BY MEMBERS OF THE DRS SPECIAL INTEREST GROUP ON EXPERIENTIAL KNOWLEDGE AND SUPPORTED BY THE DESIGN RESEARCH SOCIETY.

ORGANIZING & PROGRAM COMMITTEE

Mary Karyda , Moholy-Nagy Universtiy of Art and Design
Damla Çay, Moholy-Nagy Universtiy of Art and Design
Renáta Dezső, Moholy-Nagy Universtiy of Art and Design
Ágnes Karolina Bakk, Moholy-Nagy Universtiy of Art and Design
Jessica Hemmings, University of Gothenburg
Nithikul Nimkulrat, OCAD University, Canada

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Ádám Szabó exhibition chair

Natália Pass project manager
Judit Kollár event manager
Vivien Andavölgyi project manager

Király Bálint graphic designers

CONFERENCE THEME

Over the centuries our understanding of what constitutes data has – and continues today – to shift. In the 18th century, datum, the singular of data, referred to a piece of information through which inferences could be drawn. For the scientific community, the focus shifted from receiving what is given to extracting what is not. Data transitioned from an entity that was previously unknown or unexplored to being the epitome of what scientists strive to uncover via systematic investigation and observation.

More recently, the art and design community's engagement with data has once again shifted understanding of the term. Data became an experimental medium for artists and designers and data literacy of general audiences began to emerge. These changes have prompted a more nuanced understanding of the term. Beyond the purely quantitative, data are now recognised to carry temporal and emotional qualities that can be meaningful, malleable and evocative.

Making with data is no longer exclusively digital. Data appear in hybrid and physical forms that invite various perspectives, interpretations, and reflections. For example, data can be found in physical forms like 3D-printed models, sculptures, or even tactile exhibits in museums. In addition, users can explore the embodied nature of data in virtual environments, offering unique perspectives on data's virtual materiality and influencing our perception of scale, complexity, and interconnections between humans and data. Data are no longer exclusively a scientific output either but instead appear in art and design accessible to entirely different publics. The growth of self-tracking technologies now allows anyone to track, experiment with, and explore data in ways that extend what is known about the self and decision-making in everyday life. More recently, artificial intelligence has once again contributed to shaping our understanding of the term through the use of generative technologies. Even design education has shifted in recent years, using data to inspire, support, and expand students' projects.

Thus, the idea of data has expanded beyond its conventional scientific boundaries and has become a versatile and ever-changing medium that influences how we see the world, stimulates creative expression, and enhances our daily lives in new and remarkable ways.

THE CALL OF PAPERS ENCOURAGED CONTRIBUTIONS ON THE FOLLOWING:

What constitutes making when designing with data at various scales?

How do the cultural, social and contextual influences of data affect design processes?

How might engaging with data shift our understandings of space?

What role does data play in speculation?

Are data and material practices antithetical?

At what points in the design process does data provide inspiration?

How can data take the form of new materialities?

As in previous years, the conference call received a great international response with accepted submissions from 20 countries including Australia, Belgium, Canada, China, Denmark, Estonia, France, Germany, Greece, Hungary, India, Italy, Netherlands, Portugal, South Korea, Spain, Switzerland, Turkey, United Kingdom, USA. Submissions were interdisciplinary and stemmed from a variety of disciplines and areas. For the conference, contributions were selected in a one-stage process, comprising full paper selection, through a double-blind review process by the conference's international review panel of 66 reviewers. From the contributions, the following eight tracks emerged:

TRACK 1: Data in Education
TRACK 2: Crafting with Data
TRACK 3: Data in Health
TRACK 4: Data in Processes
TRACK 5: Sensing Data
TRACK 6: Data Cultures
TRACK 7: Data Futures
TRACK 8: Transformative Data

Each session engaged with 'data' in nuanced ways, and together the tracks encompassed a wide understanding of experiential knowledge generated through the use of data as input, process or output in practice-based research.

This year's EKSIG conference also included workshops. Proposals were selected for feasibility and relevance to the conference theme. From 14 submissions, five workshops were included:

WORKSHOP 1: What people do with data physicalizations – Flow State, Play Moods, Small Beginnings by Jacob Buur

WORKSHOP 2: Exploring Self-Narratives and Data Physicalization Practices Towards a Shared Design Vocabulary by Ginevra Terenghi and Sara Lenzi

WORKSHOP 3: Transforming Physical Movement into Digital Interaction and Puppetry Control by Kálmán Tarr

WORKSHOP 4: Framing Generative Waste as Multi-Layered Interpretive Data Towards Sustainable and Reflective Design Practices by Alice Mioni and Antonella Autuori

WORKSHOP 5: Space Oddities – Societal Effects of Phygitality by Romi Mikulinsky, Aya Bentur and Micaela Terk

An Exhibition of the MOME's students works on data were also displayed during the conference. The artworks were Title and Artist/Designer... Last, Hajnal Gyeviki's participatory data physicalization titled Balaton Borders was exhibited but also included in the final performance of the conference during the closing event.

An exhibition of MOME students' works on data, alongside works by the Dataweavers collective, was also displayed during the conference.

TRACK 8:

TRANSFORMATIVE DATA

Chair: Ágnes Bakk, Researcher, Moholy-Nagy University of Art and Design

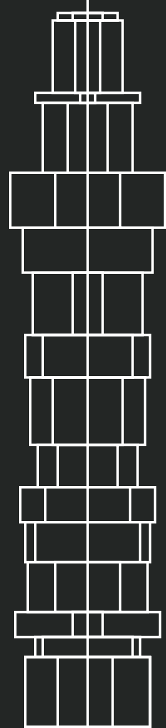
PAPERS:

THE FUTURE OF THE FOOTWEAR INDUSTRY: BIBLIOMETRIC AND SYSTEMATIC ANALYSIS OF LITERATURE FROM 2018 TO 2023
-Miguel Terroso, Adriana Amorim and Ivo Rodrigues

RICHNESS AND AMBIGUITY: MAPPING ARTIFICIAL INTELLIGENCE LABELS IN HUMAN-AI COLLABORATION RESEARCH
-Fabio Antonio Figoli, Alessandra Facchin, Beatrice Gobbo and Francesca Mattioli

TOWARDS DISTRIBUTED CREATIVITY: UNDERSTANDING GENERATIVE AIIN THE CONTEXT OF DESIGN PHILOSOPHY AND THE MATERIAL TURN
-Ákos Schneider and Dávid Csűrös

EXPERT INSIGHTS INTO XR AND URBAN DIGITAL TWINS: SHAPING FUTURE PHYGITAL CULTURAL EXPERIENCES
-Vahide Sena Çoban and Asım Evren Yantaç



RICHNESS AND AMBIGUITY: MAPPING ARTIFICIAL INTELLIGENCE LABELS IN HUMAN-AI COLLABORATION RESEARCH

Fabio Antonio Figoli
Department of Design, Politecnico di Milano

Alessandra Facchin
Department of Design, Politecnico di Milano

Beatrice Gobbo
Department of Design, Politecnico di Milano

Francesca Mattioli
Department of Design, Politecnico di Milano

Citation

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RICHNESS AND AMBIGUITY: MAPPING ARTIFICIAL INTELLIGENCE LABELS IN HUMAN-AI COLLABORATION RESEARCH

Fabio Antonio Figoli, Department of Design, Politecnico di Milano, Italy.
Alessandra Facchin, Department of Design, Politecnico di Milano, Italy.
Beatrice Gobbo, Department of Design, Politecnico di Milano, Italy.
Francesca Mattioli, Department of Design, Politecnico di Milano, Italy.

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Abstract

Artificial intelligence has rapidly gained prominence across industries and academia. However, its swift diffusion, coupled with the interdisciplinary nature of related studies, has resulted in fragmented literature, making it challenging to align diverse perspectives under shared and identifiable research trajectories. This challenge became evident while working with data from a systematic literature review we previously conducted on artificial intelligence in human-AI collaboration studies within design-related fields. Building upon this dataset, we examined how researchers label artificial intelligence in their work, recognising terminology as a central factor contributing to this fragmentation. Through an exploratory study, we identified 79 unique labels, categorising them into primary and secondary keywords. Using this data, we developed a tripartite network visualisation to map the relationships between these labels, offering insights into their specificity and the perspectives they represent. To examine the network's interpretive potential, we engaged three design researchers in a hands-on activity, analysing how they navigated the network in relation to their research work. The findings of this study highlight the value of labels as a positional tool capable of reflecting both the richness and ambiguity of the discourse. Our analysis suggests that the network can aid practical applications, such as clarifying terminology, situating research within the broader field, stimulating critical reflection, and fostering collective discussions. Our main contribution to knowledge lies in presenting a novel framework for addressing the fragmentation of artificial intelligence literature. By reflecting on how labels and their interconnections can uncover underlying research trajectories, this framework fosters alignment while valuing and clarifying the multiplicity of perspectives, moving away from pursuing a singular, unified view.

Artificial Intelligence; Labels; Human-AI Collaboration; Network Visualization; Design Research.

Artificial intelligence has experienced significant growth in recent years. Its advanced capabilities, paired with increasing accessibility, have enabled its integration across various scales, from large industries (Haefner et al., 2023) and public institutions (Henman, 2020; Reis et al., 2019; Wirtz et al., 2019) to small startups (Garbuio & Lin, 2019) and individual users. This rapid and widespread diffusion of AI has become a focal point of several academic research fields, as shown by the numerous studies addressing it recently (Hajkowicz et al., 2023).

While each new perspective broadens the discourse and introduces valuable insights, it also complicates the task of integrating these insights into a cohesive understanding. Consequently, the literature tends to become more complex, with discourse trajectories that are challenging not only to follow but also to identify clearly (Montuori, 2013). Artificial intelligence presents multiple faces, with its definition and boundaries influenced by the perspectives and priorities of the actors and stakeholders addressing it. In the context of academic research, these actors are primarily the researchers themselves, whose approaches to artificial intelligence are shaped by their disciplinary backgrounds, perspectives, and the scope of their projects. As a result, the way artificial intelligence is discussed can vary significantly across studies (Martínez-Plumed et al., 2018).

It is little surprise that artificial intelligence does not have a shared definition. Wang (2019) argues that finding a single definition for artificial intelligence could enable policymakers to assess artificial intelligence's potential and determine desirable applications (Bhatnagar et al., 2018), foster clarity within the academic community to align goals, evaluation criteria, and collaborative efforts (Monett & Lewis, 2018), and prevents conflicts arising from incompatible interpretations within research projects. Over the years, many researchers and institutions (EU, 2024) have attempted to establish a definition that could work for everyone, but whether this goal is ultimately achievable remains uncertain. As long as artificial intelligence continues to have unclear research boundaries and fragmented perspectives, consolidating all views under a single, comprehensive definition will likely remain an elusive task.

This complexity becomes even more pronounced when considering the discipline of design, which is characterised by fluid boundaries and diverse approaches spanning from humanities to hard sciences (McMahon, 2012; Rampino, 2022). As a result, the varied perceptions of artificial intelligence are further accentuated in the context of a transdisciplinary field (Montuori, 2013). The inherently ambiguous nature of design (Rampino, 2022) intersects with the ambiguous nature of artificial intelligence, leading to an even less defined understanding of how artificial intelligence is treated within this discipline.

In a context where establishing a shared definition of artificial intelligence proves difficult, we believe labels offer a practical alternative. As Connell (2019) notes, labels act as "linguistic shortcuts", providing conceptual representation of underlying concepts. As such, labels are more than linguistic tools; they embody implicit knowledge and enable alignment among members of a community (Gelman & Roberts, 2017). Unlike definitions, which strive for comprehensive and unified explanations, labels accommodate multiple interpretations within the same discourse. This flexibility fosters plurality while easing the pressure to converge on a singular definition. Labels are not peripheral to concepts; instead, they play a fundamental role in shaping how ideas are processed and communicated.

Acknowledging the value of labels, we conducted a study guided by the research question *"How do researchers in the field of human-AI collaboration in design label artificial intelligence in their work?".* In our study, labels reflect the diversity of perceptions about artificial intelligence, fostering a shared conceptual ground by synthesising diverse perspectives and shaping them into an aggregated representation. Such representation was achieved through data collection, curation, and visualisation processes, using data and their visualisation as tools for knowledge production. In this context, it is crucial to understand labels as the result of an interpretive process of collection, manifesting through various forms of representation. The interpretations become layered over time, and the collection and representation of data not only help interpret these layers but also challenge their ontologies and meanings (Hinrichs et al., 2019). Therefore, we emphasise the role of the network visualisation produced as an epistemological tool for a highly qualitative and deeply situated dataset (Drucker, 2014).

By building on this interpretive approach, our study does not seek to establish a definitive synthesis of AI terminology but rather to explore its variations within the field. Given this focus, it takes the form of an exploratory inquiry into terminology variation, with findings that should be interpreted as preliminary rather than conclusive. The study's core contribution lies in illustrating the multiple ways artificial intelligence is conceptualised in design research. Our analysis highlights how terminologies reflect both the richness and ambiguity of the artificial intelligence discourse, suggesting that labels function not only as linguistic markers but also as instruments of positionality, situating researchers' perspectives within the broader discourse.

Methodology

The three main objectives of this study were achieved through corresponding research outputs: data collection and curation, data visualisation, and data visualisation exploration (Figure 1).

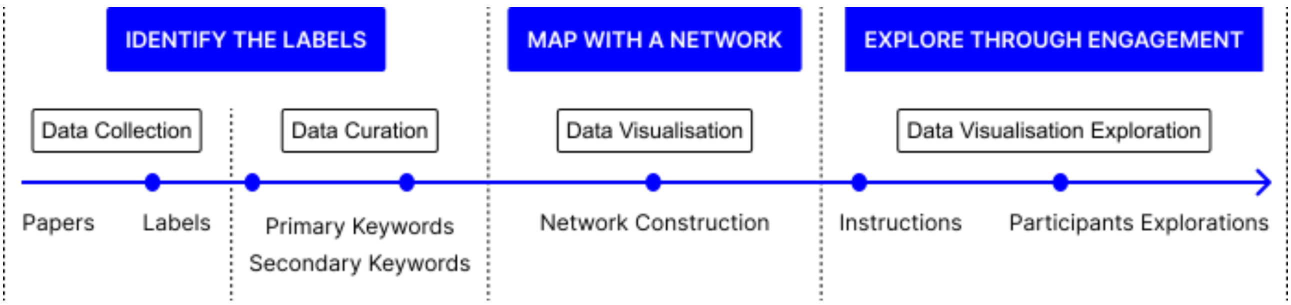

Figure 1: Methodological protocol of the study, combining objectives, outputs, and data.

Data Collection and Curation

To compile the dataset for this study, we used a corpus of publications previously gathered through a systematic literature review we conducted following the PRISMA model (Page et al., 2021). The original review, performed in 2023 using the Scopus database, aimed to explore the main discourse trajectories regarding human-AI collaboration within design-related fields. The review resulted in a final corpus composition of 48 studies, from which we extracted data on artificial intelligence labels.

To do so, we adopted a semi-automatic procedure composed of three steps. First, to ensure data gathering accuracy, we cleaned all the publication documents by removing all the content external to the main text, such as layout elements, references, and authors or publisher information. Second, we used the mixed-methods analysis software "MAXQDA" (VERBI, 2024) for word counting, which produced a list of words ordered by frequency for each publication. Additionally, for each word, the software identified the most common pairings, showing combinations of up to three words. Third, we manually reviewed each publication's word list to identify terms researchers used to refer to artificial intelligence or as its substitute, appearing at least five times.

As shown in Figure 2, we organised the dataset into three columns. The first (ID) contains the title of the publications. The second column (KW1) represents what we refer to as primary keywords. These are substantives that hold meaning independently, such as “AI”, “system”, or “agent”. Terms like “machine learning” and “deep learning” are also categorised as primary keywords due to their standalone clarity. Finally, the third column (KW2) contains what we call secondary keywords. These composite labels consist of a primary keyword combined with an additional term. In our interpretation, the combinations of two primary keywords (e.g., “AI system”) are also classified as secondary.

A	B	C
ID	AI-KWS 1	AI-KWS 2
A cautionary tale about the impact of AI on huma	AI	
A cautionary tale about the impact of AI on huma	AI	DEEP LEARNING AI
A cautionary tale about the impact of AI on huma	DEEP LEARNING	
A cautionary tale about the impact of AI on huma	DEEP LEARNING	DEEP LEARNING AI
A differential game approach to dynamic competi	MODEL	
A framework to study human-AI collaborative des	AGENT	INTELLIGENT AGENT
A framework to study human-AI collaborative des	MODEL	
A framework to study human-AI collaborative des	ASSISTANT	COGNITIVE ASSISTANT
A Situation Awareness Perspective on Human-AI	AGENT	
A Situation Awareness Perspective on Human-AI	AGENT	INTELLIGENT AGENT
A Situation Awareness Perspective on Human-AI	AGENT	AI AGENT
A Situation Awareness Perspective on Human-AI	AI	
A Situation Awareness Perspective on Human-AI	AI	AI SYSTEM
A Situation Awareness Perspective on Human-AI	AI	AI AGENT
A Situation Awareness Perspective on Human-AI	SYSTEM	
A Situation Awareness Perspective on Human-AI	SYSTEM	AUTOMATED SYSTEM
A Situation Awareness Perspective on Human-AI	SYSTEM	COMPLEX SYSTEM
A Situation Awareness Perspective on Human-AI	SYSTEM	AI SYSTEM
A Situation Awareness Perspective on Human-AI	SYSTEM	AUTONOMOUS SYSTEM

Figure 2: A section of the dataset showing the three columns “ID”, “AI-KWS1”, and “AI-KWS2”.

Data Visualisation and Network Exploration

The tripartite network was developed using the software Gephi. The arrangement of nodes and connections is defined by ForceAtlas2 (Jacomy et al., 2014), a spatialisation algorithm which brings connected elements closer together and distances unconnected ones. Moreover, the ForceAtlas2 algorithm has the “*ability to display the spatialisation process, aiming at transforming the network into a map*” (Jacomy et al., 2014, p. 1), providing essential affordances for navigation and exploration of a complex area and controversial issue like human-AI collaboration.

In particular, the network exploration revealed its potential to build exploratory pathways in line with the metaphor of maps and cartography (Mauri, 2015). We sought input from other design researchers to investigate this potential without relying solely on our interpretations—which might inadvertently introduce bias. We involved three design researchers at different stages of their academic careers: one PhD candidate at the outset of their research, one PhD candidate in the middle of their doctoral work, and a postdoctoral researcher. All three are actively involved in studies concerning artificial intelligence within the design realm. We encouraged these researchers to explore the network in their own ways, using principles from Visual Network Analysis (Venturini et al., 2021) and controversy mapping (Venturini & Munk, 2021) as guides. This approach allowed us to examine how the network can serve not only as a map of artificial intelligence terminology but also as a cognitive and reflective tool for researchers.

The study included two main phases. In the first phase, participants engaged in an exploratory mapping exercise designed to examine how they interacted with and interpreted the AI-related network. Using a printed version of the network and a marker, they were asked to trace pathways between artificial intelligence labels relevant to their work. This activity aimed to externalise their perspectives, uncover implicit connections, and provide insights into how they positioned their research within the broader discourse. Participants followed a structured set of rules: i) Choose a primary keyword from the list without viewing the complete network; ii) Start from the selected primary keyword and connect relevant secondary keywords without crossing over to a different primary keyword; iii) Explore until all keywords of interest have been covered or no further connections are possible; iv) Restart the process to create up to three distinct paths. To capture the participants' real-time thought processes while navigating the network, we employed the think-aloud protocol to record their verbal reflections and generate transcripts for the analysis.

In the second phase, participants reflected on their mapping experience by responding to three open-ended questions: *"Could you locate your research within the network?"*, *"Did anything about the network surprise you?"* and "*How might you incorporate this network into your future research?."* These questions helped assess the network's role in research positioning, facilitating sense-making, and encouraging critical reflection on terminology use.

Results

Dataset

PRIMARY KEYWORDS
AGENT - AI ALGORITHM - ASSISTANT - COMPUTER - DEEP LEARNING - MACHINE - MACHINE LEARNING - MODEL - PARTNER - ROBOT - SYSTEM - TEAMMATE - TECHNOLOGY - TOOL
SECONDARY KEYWORDS
AI AGENT - CO-CREATIVE AI - HUMAN-CENTERED AI - AI APPLICATION - CO-CREATIVE ROBOT - INTELLIGENT AGENT - AI DESIGN - CO-CREATIVE SYSTEM - INTELLIGENT ASSISTANT - AI MODEL - CO-CREATIVE TOOL - INTELLIGENT SYSTEM - AI PARTNER - COGNITIVE ASSISTANT - INTELLIGENT TOOL - AI PROCESS MANAGER - COLLABORATIVE IDEATION PARTNER - LANGUAGE MODEL - AI SOLUTION - COLLABORATIVE IDEATION TOOL - LOW-PERFORMING AI - AI SYSTEM - COMPLEX SYSTEM - MACHINE LEARNING ALGORITHM - AI TEAMMATE - COMPUTATIONAL AGENT - MACHINE LEARNING MODEL - AI TECHNOLOGY - COMPUTATIONAL MODEL - MACHINE LEARNING SYSTEM - AI TOOL - COMPUTATIONAL TOOL - NON HUMAN AGENT - AI-ENABLED TOOL - COMPUTER AGENT - OPERATION AGENT - AI-INFUSED SYSTEM - CREATIVE AGENT - PARTNER SYSTEM - ARTIFICIAL AGENT - CREATIVE SYSTEM - PREDICTIVE MODEL - ASSISTIVE AI AGENT - DEEP LEARNING AI - REGRESSION MODEL - AUTOMATED SYSTEM - DEEP LEARNING FRAMEWORK - ROBOT AGENT - AUTONOMOUS AGENT - DESIGN AGENT - SOCIAL ROBOT - AUTONOMOUS SYSTEM - ETHICAL AI - SPEECH2MINDMAP ALGORITHM - BOUNDARY-CROSSING AGENT - EXPLAINABLE AI - SUPPORT TOOL - BOUNDARY-CROSSING ROBOT - EXPLAINABLE AI ALGORITHM - TEAM MEMBER AGENT - CO-CREATIVE AGENT - HIGH PERFORMING AI - TRUSTWORTHY AI

Figure 3: The list of KWs1 and KWs2 present in the publications.

Our study's first result is the dataset that serves as the foundation for network visualisation and exploration. Here, we can highlight four results:

1. The total collected labels are 79, divided into 15 primary and 63 secondary keywords (Figure 3).
2. Connections between primary and secondary keywords show varying levels of association, with terms like "AI" and "agent" having the highest

number of connections, appearing 23 and 16 times, respectively. In contrast, others, such as “computer” and “machine,” are linked only once (Figure 4).

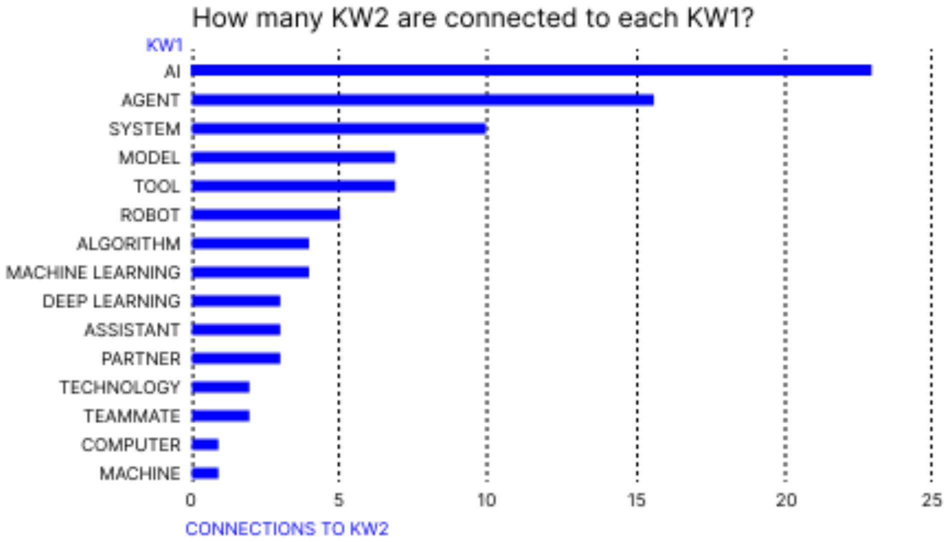

Figure 4: Number of secondary keywords connected to each primary keyword.

3. Appearances of primary keywords across publications show distinct levels of frequency, with “AI” having the highest presence, appearing in over 30 publications, followed by terms like “model,” “agent,” and “system,” which feature in more than 10 publications (Figure 5). Other terms, such as “deep learning”, “technology”, “tool”, “teammate”, “robot”, “algorithm”, “machine learning”, and “assistant”, appear in fewer than 10 publications, while “computer” and “partner” are observed only once.

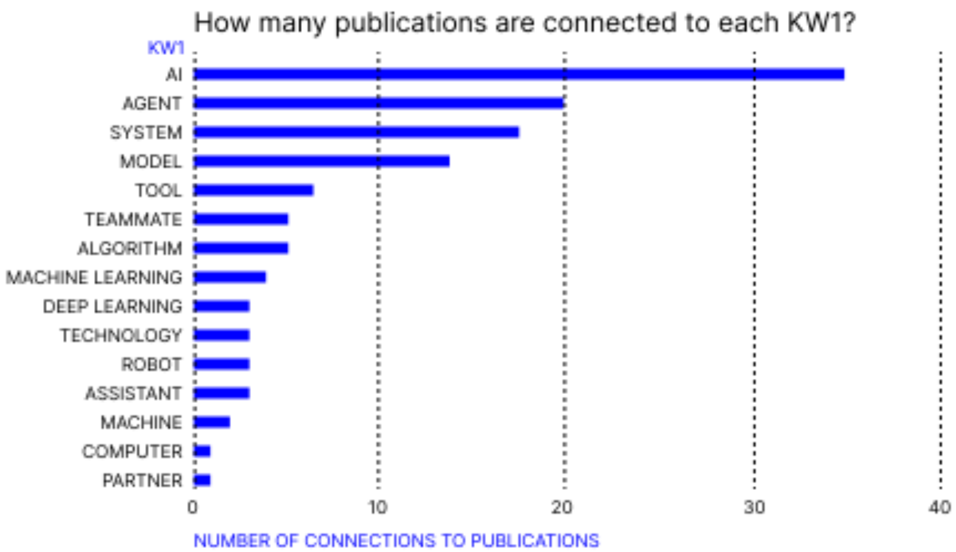

Figure 5: Number of publications including each primary keyword.

4. Primary keyword usage diversity in each publication can be grouped into

three levels, as shown in Figure 6. Eight publications use one primary keyword label throughout. 23 publications employing two or four primary keywords. 17 publications present five or more primary keywords.

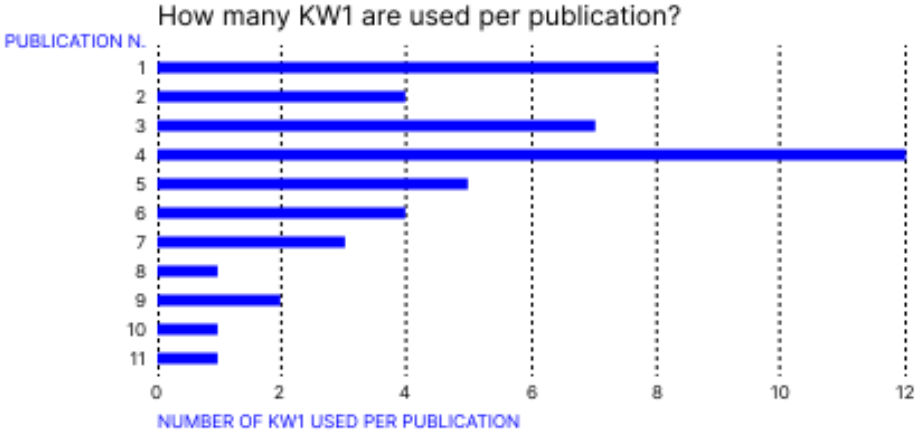

Figure 6: number of primary keywords used per publication.

Network Visualisation

Primary Keywords Disposition

The network visualisation represents the second key output of our study, mapping the spatial arrangement of primary and secondary keyword nodes along with their connections (Figure 7). The spatial disposition of the nodes in the network, especially the primary keyword ones, allowed us to identify two clustering of interest: concentric (Figure 8) and vertical (Figure 9).

In the *concentric clustering*, using “AI” as the central reference point, two outward-expanding clusters emerge: the *inner cluster* comprising the primary keywords “system”, “agent”, “technology”, and “model”. Surrounding this, the *outer cluster* includes a broader array of terms, such as “tool,” “assistant,” “robot,” “teammate”, “computer”, “deep learning”, “machine”, “algorithm”, “machine learning”, and “partner”.

In the *vertical clustering*, examining the primary keywords' vertical spatial arrangement reveals two distinct clusters. Using “AI” as the central reference point, we observe a clear division: the *bottom cluster*, positioned at the lower end, includes keywords such as “model”, “deep learning”, “machine learning”, “machine”, and “algorithm”, reflecting a focus on computational and functional aspects of artificial intelligence. In contrast, the *top cluster*, located at the upper end, comprises keywords such as “tool”, “assistant”, “agent”, “robot”, and “teammate”, emphasising artificial intelligence’s role in human interactions.

Within these broader clusters, more nuanced sub-clusters can be identified based on thematic orientation (Figure 9): the *technical cluster* (“deep learning”, “machine learning”, “machine,” and “algorithm”), the *relational cluster* (“tool”, “assistant”, “agent”, “teammate”, and “partner”), and the *physical cluster* (“robot”). In contrast to these, a central group of broadly applicable keywords, such as “AI”, “system”, “model”, “technology”, and “computer”, lacks a specific thematic orientation. We refer to this grouping as the *tautological cluster*.

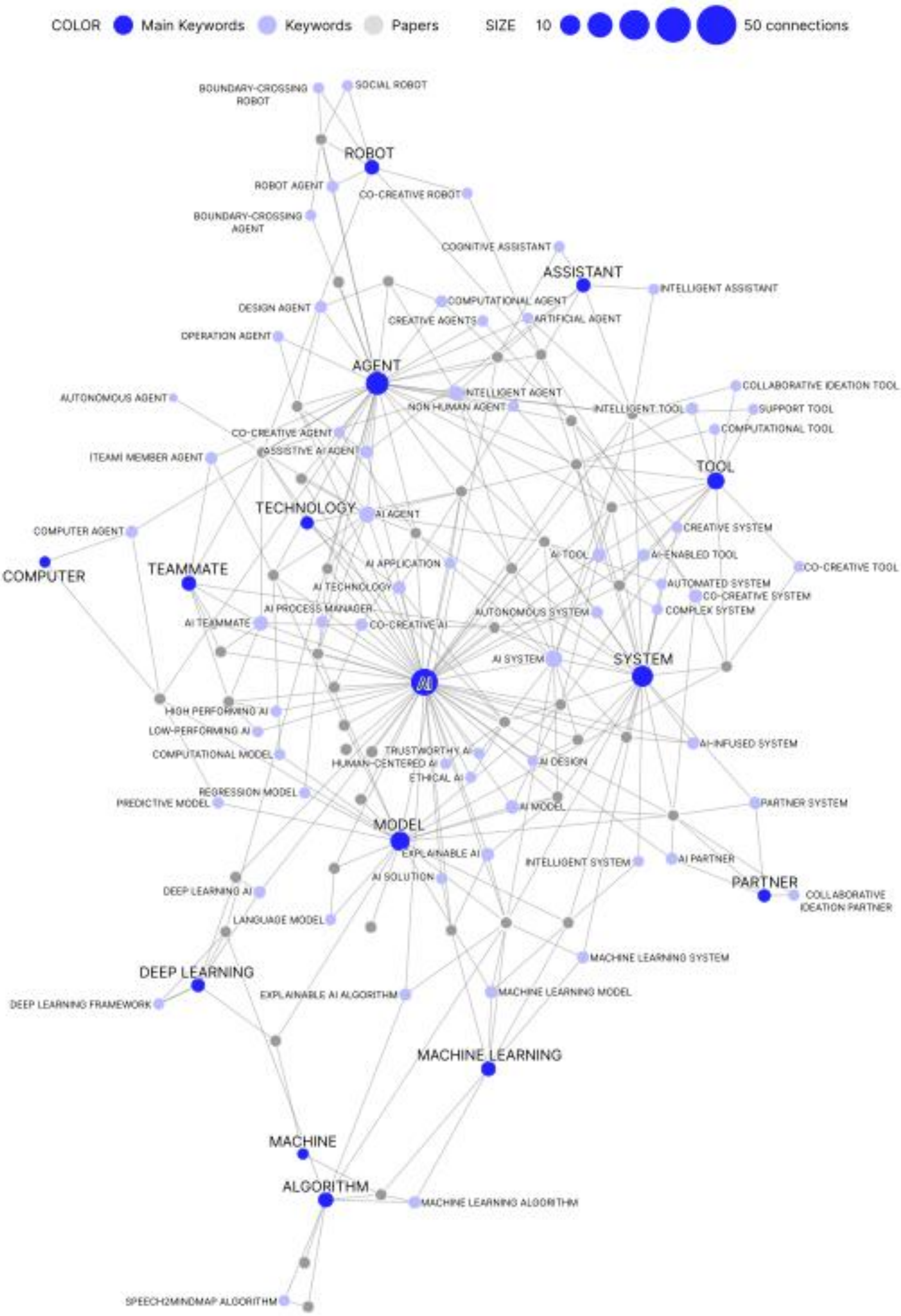

Figure 7: The Artificial Intelligence keywords network.

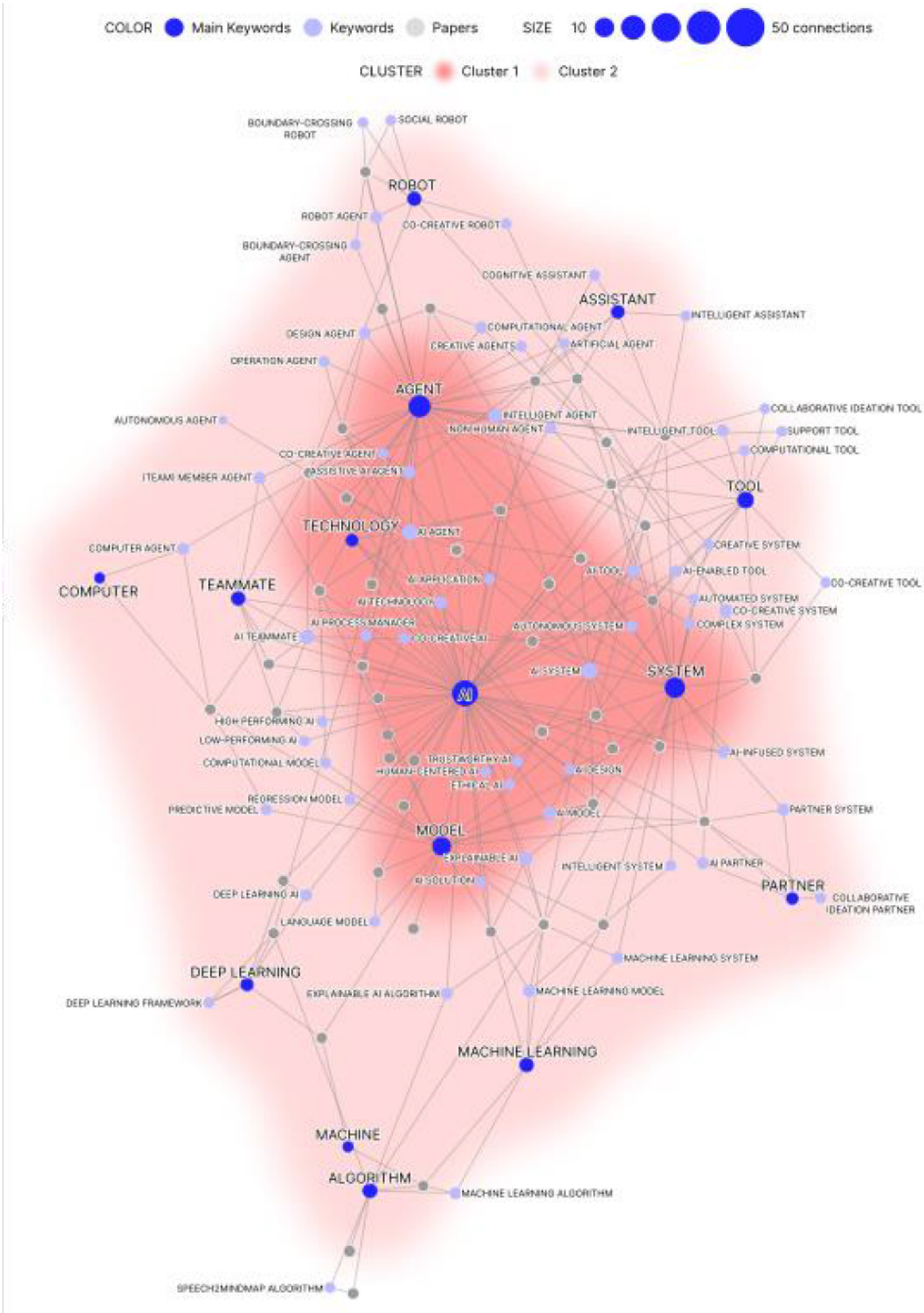

Figure 8: The Artificial Intelligence keywords network with concentric clustering.

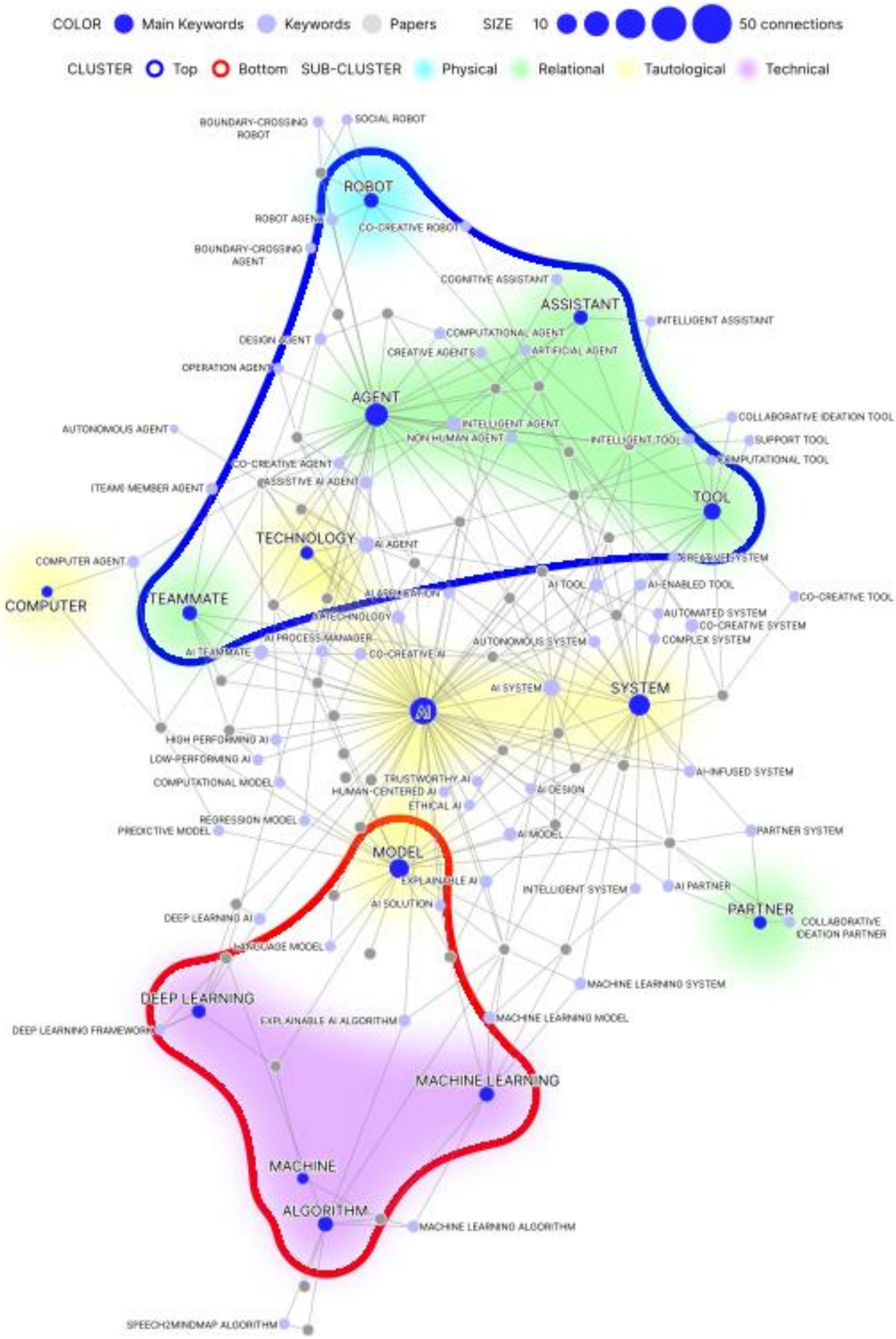

Figure 9: The Artificial Intelligence keywords network with vertical clustering and sub-clusters.

Secondary Keywords Overview

The secondary keywords nodes occupy the interstitial space between primary keywords' nodes, introducing finer thematic distinctions that enhance the network's interpretive clarity. In essence, secondary keywords act as detailed extensions of primary ones, breaking broader terms into more precise and contextualised components.

For example, consider the primary keyword "tool", which suggests a perspective of artificial intelligence as "something that assists in performing a specific activity" (Dictionary Cambridge, 2024). This term may imply a hierarchical, subordinate relationship between artificial intelligence and humans, emphasising its utility and assistance. However, when "Tool" is paired with additional terms, the newly formed secondary keyword gains greater interpretive depth, enhancing its contextual meaning. This increased nuance is observable in the network, where secondary keywords such as "support tool", "collaborative ideation tool", "computational tool", "intelligent tool", "co-creative tool", "AI-enabled tool", and "AI tool" emerge, each possibly contributing to distinct layers of interpretation.

Network Exploration

Participant One

At the start of their PhD, the first participant traced the violet paths visible in Figure 10. The paths touch several areas of the network, spacing from left to right and from top to down, but almost without touching external keywords. During the network exploration, the participant found selecting both the initial primary keyword and subsequent secondary nodes challenging. They expressed uncertainty about the relevance of specific keywords to their research, leading them to explore the network more intuitively, often speculating which keywords might become interesting for their work in the future. Table 1 contains the participant's response to the open-ended question and our interpretation.

Participant Two

In the middle of their PhD, the second participant traced the orange paths visible in Figure 10. Besides the path starting from "tool", the other paths unfold mainly in the central area of the network. During the network exploration, the participant confidently traced the path, disregarding keywords irrelevant to their research. On several occasions, they deliberately bypassed entire network sections, avoiding areas associated with specific keywords not aligned with their perspective on artificial intelligence. Finally, the participant felt that some terms were vague, and some connections seemed arbitrary or lacked detailed explanations. Table 1 contains the participant's response to the open-ended question and our interpretation.

Participant Three

The third participant, a postdoctoral researcher, traced the green paths visible in Figure 10. The first path begins in the network's centre-left section, extending leftward and toward the centre. The second path originates from an external node in the upper-right area and progresses centrally. During the network exploration, the researcher confidently traced the paths, clearly explaining the reasonings behind each progression. They also noted the absence of keywords related to more-than-human theories in the network. Moreover, the participant felt the network had static connections and could benefit from a more interactive structure. Table 1 contains the participant's response to the open-ended question and our interpretation.

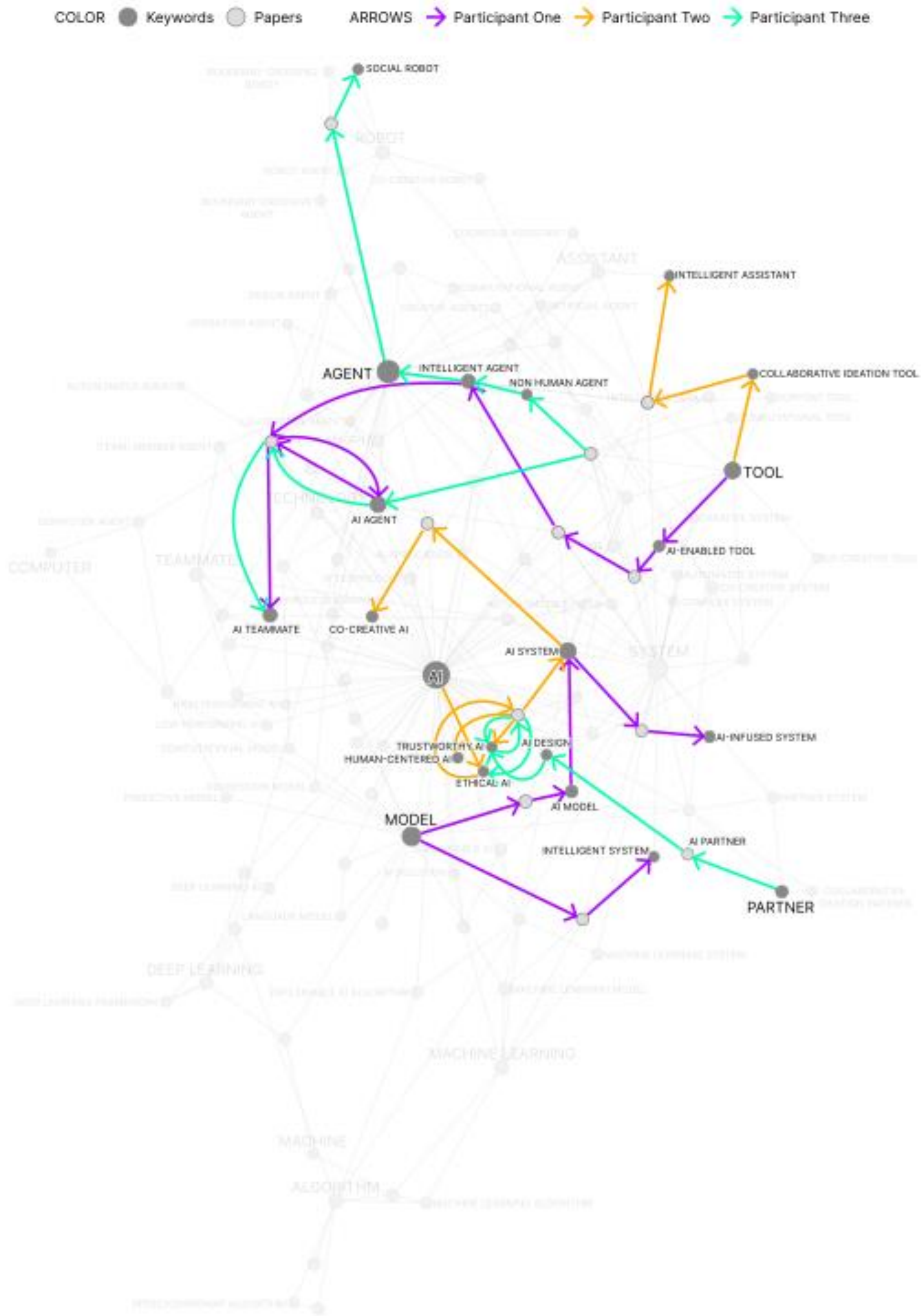

Figure 10: The network comprises the paths traced by each participant.

Table 1: Participants' answers to the open-ended questions.

Question	P	Quotes	Interpretation
Could you locate your research within the network?	1	*"Yes, I think I'm a bit in this area... I would like to place myself in an AI-infused system, but for now, I'm in a kind of grey area."*	The participant could locate their research despite acknowledging that their area of interest remains undefined.
	2	*"Yes, here, definitely between AI system, AI human-centred, explainable, ethical AI, and also trustworthy."*	The participant could locate their research, focusing on AI, human-centred, ethical, and trustworthy AI.
	3	*"Yes, for sure, I work a lot in this area; my research is right in this area where the concepts of robot and agent intersect." / "There is a part missing, like more than human, which I can't find where I would position myself."*	The participant could position their research around concepts related to robots, agents, and human-robot interaction. However, they could not find KWs related to more-than-human concepts.
Did anything about the network surprise you?	1	*"Yes, I like it; I hadn't thought about it this way. The concepts in my head are more overlapping. It's useful to think of it this way, separated, because there are larger nodes, and not all are of the same hierarchy." / "Yes, there are other perspectives, like Teammates, which is something I wouldn't expect for AI in my work... but I understand there's a lot of research on AI as a Teammate. It seems a bit far from what I'm looking for in AI, but it's valid."*	The participant was surprised by the hierarchical structure and the inclusion of unexpected concepts.
	2	*"The robot part... it's the only point where AI takes a form, like it becomes physical." / "Computer seems like a 1970s definition... like the old boxy computer." / "Teammate has a very human, equal connotation, which feels odd."*	The participant was surprised by terms like "robot," "computer," and "teammate," which felt outdated or too equal to humans.
	3	*"I don't know if it shows richness or a large ambiguity." / "Seeing machine learning here is strange... it shows a lot of confusion because I don't think machine learning means AI." / "It shows that this field is still a big work in progress."*	The participant was uncertain if the network showed richness or ambiguity due to duplicated terms and some unexpected inclusions.
How might you incorporate this network into your future research?	1	*The most direct use is to search for related terms when looking for literature... for example, I might not search for 'AI system' because I'd get 8,000 papers, so I'd go for 'AI-infused system,' which is more specific and has a different nuance."*	The network could help narrow search terms and add specificity to keywords for literature searches.
	2	*"It would be useful... especially when I started my PhD, to know terms like trustworthy AI and explainable AI." / "If I ever shift to another AI area, I would definitely reuse it."*	The participant noted the network's usefulness in identifying relevant keywords, particularly when engaging with the topic for the first time or exploring new areas within it.
	3	*"It could really help build a keyword system… if it were more dynamic, moving things around or changing connections would be amazing." / "It would be useful for positioning in a field, especially in an initial research phase."*	The participant found it helpful for research positioning and building a keyword system for literature reviews. Moreover, they suggested a more dynamic version could benefit the network's usage.

Discussion

Labels as a Research Positioning Instrument

The dataset and the network visualisation highlight a notable diversity in how researchers label artificial intelligence. Considering the relatively small sample size of publications and the focused thematic scope of human-AI collaboration, this diversity might be even more pronounced if we included a broader array of publications or explored other fields. This variability in labels is evident across different publications and individual studies.

On the one hand, this variation could imply that researchers do not prioritise consistency in how they refer to artificial intelligence, instead choosing labels serendipitously as long as they are sufficiently clear to their intended audience. On the other hand, if labels were incidental, why would so many distinct ones be produced, and why would they differ significantly? From our analysis, we propose a middle ground: while it is likely that, understandably, not all researchers reflect extensively on their choice of labels, its diversity reflects the wide-ranging scope of artificial intelligence itself. Researchers capture this diversity through their diverse labels, which reflect their perspectives, intentions, and interpretations.

Our network concentric clustering reveals that every label has a degree of meaning specificity (Figure 8). Label centrality, determined by the number of connections, shows a clear pattern: the most connected labels, positioned centrally, tend to be less meaning-specific, while labels with fewer connections, located toward the outer layers, are more meaning-specific. Therefore, whereas one moves outward from the centre, the terms gradually gain meaning specificity, focusing on narrower aspects of artificial intelligence. For instance, the central label “AI” is the least specific, the intermediate label “Model” has moderate specificity, and the outer label "Algorithm" denotes high specificity.

Moreover, complementary to meaning specificity, labels reflect a perspective. The top and bottom clusters emerging from the vertical clustering (Figure 9) reveal two distinct perspectives on artificial intelligence. The top cluster represents an *external* perspective, focusing on artificial intelligence roles in relation to humans and society. In contrast, the bottom cluster adopts an *internal* perspective, emphasising the technology’s internal workings and computational structures.

In the context of artificial intelligence—a field generating extensive debate within and beyond academia—we argue that labels could serve as positional instruments, where selecting a particular label may imply adopting a specific stance within the discourse. Labels with greater meaning specificity (e.g., “teammate”) tend to make a researcher’s position more distinct and identifiable. However, this clarity can also have polarising effects. For instance, during the network exploration, participants expressed strong opinions—both agreement and disagreement—about specialised terms such as “teammate” or “robot,” whereas broader terms elicited more neutral responses. This highlights the potential dual role of labels as both clarifiers and possible sources of division within the discourse.

“Richness or Ambiguity?”

The interplay between richness and ambiguity emerged clearly in the participants’ network exploration. As they navigated the labels, they experienced a combination of surprise—discovering new and intriguing terms—and confusion—encountering terms they did not usually associate with artificial intelligence. Certain labels, such as “robot”, were particularly polarising. For instance, one participant viewed robots as integral to artificial intelligence, and another explicitly excluded them, underscoring how labels often carry implicit disciplinary assumptions and personal perspectives.

It is important to clarify that our intention was not to validate specific labels or to propose definitive categorisations. Instead, we sought to capture and visualise how artificial intelligence has been labelled by researchers, revealing the complexity and diversity of these terminologies. This inclusive approach inevitably resulted in a dataset containing ambiguous terms—some lacking clear definitions or a direct connection to artificial intelligence, while others appeared nearly identical yet referred to subtly distinct concepts. On one hand, this diversity enriches the discussion by integrating multiple perspectives, highlighting the evolving and dynamic nature of artificial intelligence in design. On the other hand, it introduces considerable ambiguity, especially when terms lack clear definitions or when nearly identical labels refer to slightly different concepts.

While participants generally perceived the network positively and acknowledged its applicability in their research, they also recognised the challenge of navigating and interpreting label diversity. Consequently, labels do not merely reflect the richness of the field but also reinforce its ambiguity, potentially perpetuating uncertainty rather than resolving it.

This issue, even if fundamentally conceptual, carries practical consequences. A wide variety of artificial intelligence labels complicates efforts to track and categorise relevant terms systematically, which is particularly critical when considering our academic system that relies on keywords and textual indexing (Mattioli et al., 2023; Stappers et al., 2023). For instance, a researcher conducting a literature review on artificial intelligence may inadvertently overlook entire segments in the literature simply because key terms were absent from their search criteria.

Network as a Tool to Navigate Ambiguity and Beyond

Initially, we built the network to analyse how researchers label artificial intelligence in their studies. However, as the network evolved and the participants’ exploration was conducted, its potential expanded beyond its original purpose. In particular, the network may act as a tool to navigate ambiguity in artificial intelligence research and literature. Participants highlighted this potential, identifying four key actions the network can facilitate:

Clarifying terminology. While the study does not establish definitive terminology refinement, participants found the network useful for narrowing broad labels, such as shifting from “AI system” to the more specific “AI-infused system.” This suggests that the visualisation may support more targeted term selection in research queries.

Research Positioning. The network offered participants a way to explore and situate their research focus within the broader landscape of artificial intelligence-related labels, helping them contextualise their work in relation to other conceptualisations of artificial intelligence. Notably, participants engaged with the network in varying ways depending on their research stage, suggesting that their approach to navigating the network might be influenced by the level of development in their study.

→ The first participant, at the outset of their PhD, explored potential future terms of interest by tracing paths that remained within central nodes—labels broader in scope and less meaning-specific.

→ The second participant, at an advanced stage of their PhD, navigated the network with a logic of exclusion, deliberately avoiding terms outside their scope of interest and similarly staying within central nodes.

→ The third participant, a postdoctoral researcher, followed a logic of inclusion, focusing on terms that aligned with their interests. Their paths frequently touched external and more polarising nodes, reflecting a preference for more specialised and meaning-specific labels.

Stimulating reflection. The network encouraged participants to critically engage with diverse perspectives surrounding artificial intelligence. They expressed surprise or confusion regarding the inclusion or exclusion of specific labels, prompting them to question their assumptions about artificial intelligence terminology and the correspondent perspectives.

Facilitating collective discussion. Although participants did not engage in collective reflection during the test—since it was conducted individually and asynchronously—we argue that the network holds potential as a boundary object for fostering collective discussion and alignment. By overlaying the individual paths into a comprehensive visualisation (Figure 10), the network enables direct comparison, highlighting intersections and divergences in participants' perspectives and focus areas related to artificial intelligence. This shared visualisation can serve as common ground for stimulating dialogue, enhancing mutual comprehension and fostering collaborative exploration.

Conclusions

This study explores how researchers in the field of human-AI collaboration in design label artificial intelligence in their work, aiming to tackle the issue of fragmented artificial intelligence literature and definition. Through qualitative analysis and the visualisation of these labels in a comprehensive network, we have highlighted how terminologies may reflect the multifaceted nature of artificial intelligence, which can be understood both as rich and ambiguous. In this context, labels function not merely as linguistic tools but also as an instrument of positionality, capturing researchers' perspectives and shaping their contributions to the broader discourse. Finally, we observed how the network visualisation of the labels can serve as an analytical tool for navigating better such complexity. In particular, the participants' network exploration suggested its potential for clarifying terminology, research positioning, stimulating reflection, and facilitating collective discussions.

However, it is worth mentioning that this study has certain limitations, which open opportunities for future research. The dataset's specific focus on human-AI collaboration, our approach used for processing the data—one among many possible methods— and the small participant sample set this study as exploratory. Therefore, its findings should be regarded as preliminary rather than conclusive.

Future work should address these limitations by scaling the methodology to encompass more extensive and diverse datasets, broadening its applicability to a broader range of research contexts. Additionally, improving the network visualisation's readability and navigability is crucial. Transforming the network into a dynamic, interactive tool could significantly enhance its potential for interdisciplinary collaboration. Such advancements would allow researchers to align their perspectives better, navigate ambiguity, and promote greater clarity and cohesion within artificial intelligence-related discussions.

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Fabio Antonio Figoli

is a PhD candidate in the Department of Design at Politecnico di Milano. His research explores the evolving interaction dynamics between designers and artificial intelligence within the design process. Beginning with his master's thesis in 2021, he has investigated how artificial intelligence integration is reshaping design practice, particularly regarding team collaboration. His PhD research further examines how designers incorporate generative artificial intelligence into their workflows, analysing interaction patterns, its impact on design processes, and implications for professional identity.

Alessandra Facchin

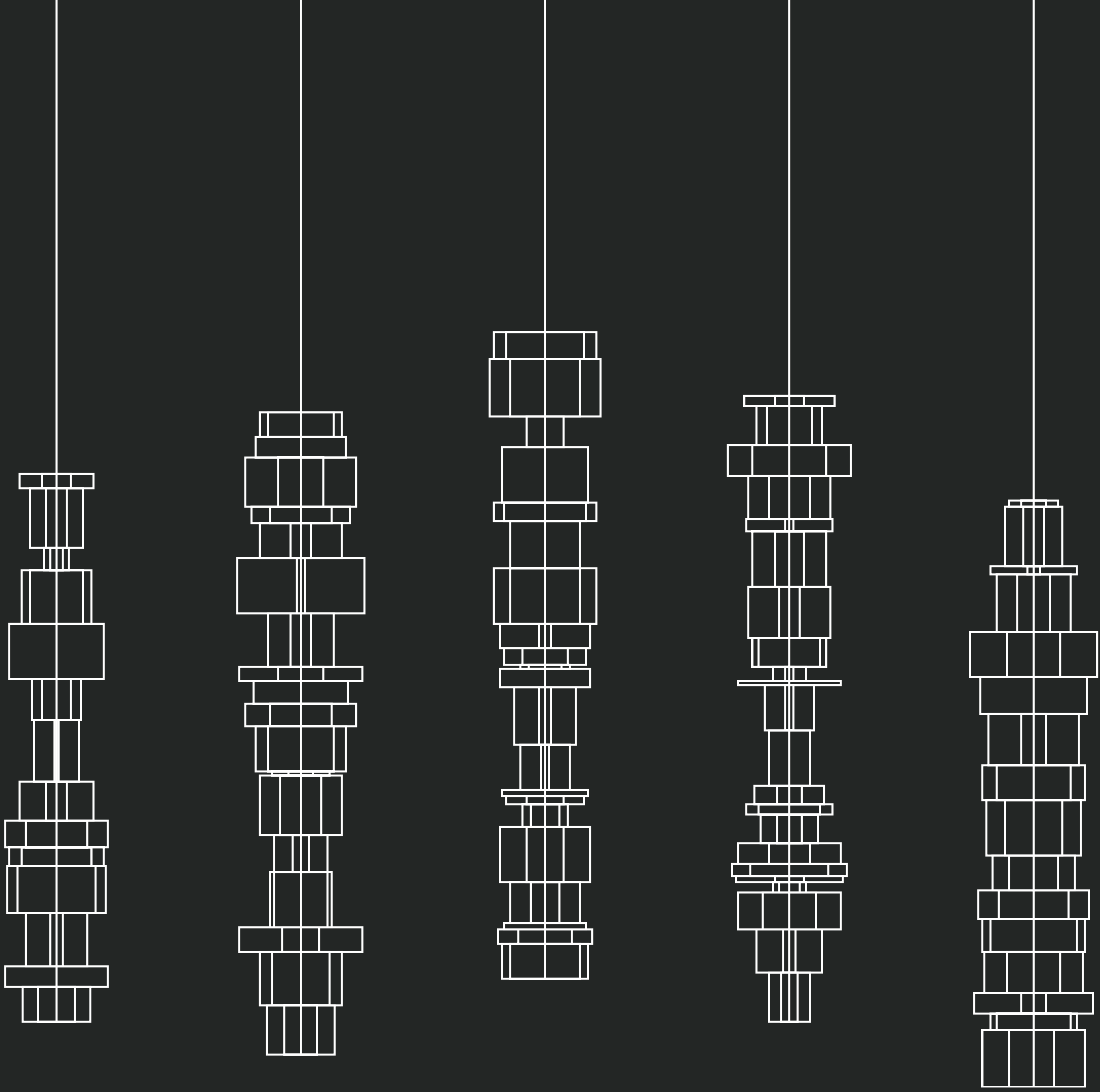
is an information designer and a PhD candidate at DensityDesign Research Lab, Department of Design, Politecnico di Milano. Her research is about leveraging information design and data visualization to communicate scientific themes to expert audiences. Her focus is the perception of urban biodiversity on social media platform, how to study this phenomenon online and how to inform scientists about it.

Beatrice Gobbo

Her research lies at the intersection of data visualization, information design and social sciences. Since 2018, she has been actively involved in teaching and contributing to international projects, including AlgoCount, founded by Fondazione Cariplo, ShapingAI founded by UKRI, and AI in the Street funded by BRAID. She has collaborated with international research groups such as CIM, Public Data Lab, Digital Methods Initiative, and Tracking Exposed, underscoring her commitment to transdisciplinary approaches. During her PhD, she investigated how information design could help visually explain artificial intelligence to non-expert audiences. Currently, within the Horizon Europe-funded NeuroClima project, she investigates the nexus between artificial intelligence, sustainability, and citizen engagement.

Francesca Mattioli

Her research focuses on applying designerly ways of thinking to build compelling and effective instructional projects. During her PhD, she focused on instructional design to foster the development of designers' cross-cultural collaborative competences through project-based learning. In her post-doc, she focused on PhD in Design education being involved in the EU-funded Erasmus+ project DoCS4Design - Doctoral Courses System for Design. Also, she researched the role of experimentation in innovating teaching and learning practices in situated contexts. Within the project MICS, funded by the Italian Ministry of University and Research thanks to the NextGeneration EU funding, she is currently contributing to developing a capacity-building model for Italian manufacturing companies in the fashion and furniture sector to promote more circular and sustainable practices.



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