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AI Methodology Map. Practical and Theoretical Approach to Engage with GenAI for Digital Methods Research

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Abstract

This essay accounts for a novel way to explore generative artificial intelligence (GenAI) applications for digital methods research, based on the AI Methodology Map. The map is a pedagogical resource and a theoretical framework designed to structure, visually represent, and explore GenAI web-based applications. As an external object, the map functions as a valuable teaching material and interactive toolkit. As a theoretical framework, it is embodied in a static representation that provides principles for engaging with GenAI. Aligned with digital methods' practical, technical, and theoretical foundations, the map facilitates explorations and critical examinations of GenAI and is supported by visual thinking and data practice documentation. The essay then outlines the map principles, its system of methods, educational entry points, and applications. The organization is as follows: First, we review GenAI methods, discussing how to access them, and their current uses in social research and the classroom context. Second, we define the AI Methodology Map and unpack the theory it embodies by navigating through the three interconnected methods constituting it: making room for, repurposing and designing digital methods-oriented projects with GenAI. Third, we discuss how the map bridges GenAI concepts, technicity, applications and the practice of digital methods, exposing its potential and reproducibility in educational settings. Finally, we demonstrate the AI Methodology Map's application, employing a digital methodology to analyze algorithmic race stereotypes in image collections generated by nine prominent GenAI apps. In conclusion, the essay unveils methodological challenges, presenting provocations and critiques on repurposing GenAI for social research. By encompassing practice, materiality and theoretical perspective, we argued that the AI Methodology Map bridges theoretical and empirical engagement with GenAI, serving them together or separately, thus framing the essay's main contribution. We expect that the AI Methodology Map's reproducibility will likely lead to further discussions, expanding those we present here.

Keywords: Generative Artificial Intelligence; GenAI; Digital Methods; AI in Education; Image Networks; Technicity; Algorithmic Race Stereotypes.

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This essay is situated within the context of the “Designing With: A New Educational Module to Integrate Artificial Intelligence, Machine Learning and Data Visualization in Design Curricula” research project, that aims to develop and define a new educational module suitable for multidisciplinary environments to integrate Artificial Intelligence (AI), Machine Learning (ML), and Data Visualization (DV) into Design curricula. The research project was financially supported by the International Program of Movetia (https://www.movetia.ch), from September 2022 to February 2024. Movetia promotes exchange, mobility, and cooperation within the fields of education, training, and youth work — in Switzerland, Europe, and worldwide. We extend our gratitude to the project team for their contributions throughout the development of this work. A special thank you to all the students who participated in the workshops; their engagement and insights were invaluable. Thanks to Nerea Calvillo for contributing her insightful feminist perspective and comments to the case study on algorithmic race stereotypes. We also wish to acknowledge the 2023 Generative Methods Conference of Aalborg University in Copenhagen, where we first introduced the AI Methodology Map and its results.

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1 Introduction

This essay accounts for a novel way to explore generative artificial intelligence (GenAI) based on the AI Methodology Map[1]. The map is a pedagogical[2] resource (interactive toolkit and teaching material) and theoretical framework designed to structure, visually represent, and explore generative artificial intelligence (GenAI) web-based applications (apps) for digital methods-led research. In particular, the explorations of apps and code-based platforms mediating access to GenAI foundation models (Burkhardt & Rieder, 2024). The map is an interactive toolkit and teaching material to support workshops and AI sprints, and it is also embodied in a static representation which covers theoretical orientation principles for engaging with GenAI. While we

1. The map is available at https://genmap.designingwithai.ch/map and documented at https://github.com/zumatt/AI-Methodology-Map. The AI Methodology Map integrates an experimental and multidisciplinary ongoing project, namely “Designing With: A New Educational Module to Integrate Artificial Intelligence, Machine Learning and Data Visualization in Design Curricula”. It is a research project in collaboration between the Institute of Design, SUPSI; the Universidade NOVA de Lisboa, iNOVA Media Lab, and the EPFL.

2. The term pedagogical refers to the theoretical-practical framework based on Bloom’s Taxonomy (Anderson & Krathwohl, 2001), reflecting the educational approaches, practices and purposes that should characterise education in the 21st century.

expect the reader to take these perspectives together, they can also serve separate purposes if desired.

The AI Methodology Map is based on three core principles: the theoretical and practical foundations of digital methods (Marres, 2017; Omena, 2021a), visual thinking and documentation of data practices (Arnheim, 1980 & 2001; Mauri et al., 2020), and interdisciplinary research efforts (Gray et al., 2022). Unlike method protocols and recipes that present "how to" steps to achieve a specific research outcome while ensuring reliable results (see Bounegru et al., 2017), the map prioritizes ways of knowing GenAI. That is understanding *what to look at* when leveraging GenAI to advance digital methods. Therefore, the map expands established digital methods practices, i.e., enacted by the repurpose of crawling, scraping, and API calling for social and cultural research, by enquiring and experimenting with *what counts in practice* when repurposing GenAI.

The AI Methodology Map differs from quick responses to the AI impact and (mis)uses with precautionary measures, as it is not focused on mandating transparent disclosure of the use and performance of large language models (LLMs) (see Stokel-Walker & Noorden, 2023; Dwivedi et al., 2023) or promoting a framework that primarily centres on the ethical issues and misuses of GenAI in educational settings (see Russel Group, 2023; Popescu & Schut, 2023; Baidoo-Anu & Ansah, 2023). Although acknowledging these as critical factors, we argue that the effort to understand GenAI from uncomplicated and technical perspectives — as the map proposes — is equally relevant. The map, thus, addresses other challenges of "repurposing" GenAI (technology) for social research, which involves most of all, a mindset (see Franklin, 1990; Marres, 2017) encompassing conceptual, technical, and empirical dimensions (see Hoel, 2012; Omena, 2022; Rieder, 2020). By creating space for GenAI to sit through hands-on practice, the map aims to surface foundational layers in discussions for social research and contributes to the field of digital methods epistemology.

This essay outlines the AI Methodology Map principles, its system of methods, educational entry-points, and applications. The organization is as follows: First, we review GenAI methods, discussing how to access them and their current uses in social research and the classroom context. Second, we define the map and unpack the theory it embodies, navigating through the three interconnected methods constituting it: *making room for Generative AI* (method 1); *repurposing GenAI apps and outputs* (method 2); and *designing digital methods-oriented projects with GenAI outputs* (method 3). Method 1 focuses on ways to become familiar with GenAI conceptually, technically and empirically. Method 2 introduces new ways to use GenAI and repurposing prompting techniques as research methods. Method 3 elicits the exploration of designing digital methods projects for analyzing GenAI models, outputs, or interfaces. Third, we discuss how the map bridges GenAI, technicity, applications and the practice of digital methods, demonstrating its potential and reproducibility in three educational settings. Finally, a case study demonstrates the AI Methodology Map's application, employing a network vision methodology (Omena, 2021b) to analyze image collections generated by nine prominent GenAI apps. This study investigates algorithmic race stereotypes and compares visual models' responses to the same prompt. We conclude by discussing methodological challenges and addressing three provocations.

This essay's main contribution is the introduction and development of the "AI Methodology Map", a dual-purpose interactive toolkit and theoretical framework designed for exploring GenAI applications in digital methods-led research within the Social Sciences and Humanities. By functioning as both a theoretical framework and a practical tool, the map bridges a gap between theoretical perspectives and empirical engagement with GenAI, and facilitates its integration into educational and research contexts.

2 Generative AI Methods: From Definition and Accessibility to Social Research Applications and Classroom Context

GenAI is a subset of machine learning (ML) that employs deep generative models to generate novel and realistic content across various modalities (e.g., text, images, code) based on user prompts[3]. To facilitate user interaction with such models, interfaces are developed as tools that use prompts as interaction touchpoints (Banh & Strobel, 2023). Each model necessitates different types of input data and is enabled to generate specific outputs, exemplified by the functionality of input data to output data, which may include text-to-text, text-to-image and other operations. The development of generative AI is contingent upon the integration of three essential components: a dataset utilized in the training of the large language model (LLM), the source code employed to define and execute the training process on a given dataset, and the model eventually comprising the parameters or weights (Shrestha et al., 2023).

The ability of GenAI models to produce *previously unseen synthetic content* (García-Peñalvo & Vázquez-Ingelmo, 2023) differs from classification tasks performed by predictive ML models, such as identifying constitutive elements and semantic contexts in an image, e.g. person, woman, happy. GenAI models offer unpredictable synthetic content. On the one hand, the meaning of language is created through the user inputs (data or prompt) and the model's capacity to recognize existing information and generate new content (Gozalo-Brizuela & Garrido-Merchan, 2023). On the other hand, the specificity of GenAI models can shape research methodologies as what they generate exposes their internal knowledge space (see Borra, 2024; Burkhardt & Rieder, 2024).

2.1 Accessing GenAI Methods through Web Apps and Coding Platforms

The accessibility of LLMs to generate content — identified in the essay as GenAI methods — may be achieved through two distinct modes, as shown in Figure 1. One can access GenAI models through open source or proprietary (1) web applications and (2) coding platforms, which allow us to carry out tasks using the model in different ways yet requiring different skill sets.

GenAI web applications offer intuitive interfaces requiring no prior technical knowledge, such as Dall-E 2 (Ramesh et al., 2022) or ChatGPT (OpenAI, 2023) for generating images and text. That is, one accesses the GenAI methods via front-end interface interactions only. Other examples are research software web-based applications, such as Prompt Compass (Borra & Plique, 2024)[4] which provides access to various LLMs, offering a library of prompts for digital research and allowing users to apply these prompts to a series of inputs. GenAI coding platforms allow interaction with the model through code, providing more customization and often more control over the data used. This generally requires medium to high programming skills. Models can be accessed via global information trackers like GitHub or coding platforms like HuggingFace. Examples include Meta Llama 2 (Touvron et al., 2023), multiple large language models (LLMs) that have already been trained and refined, and Stable Diffusion (Rombach et al., 2021), a model that can be used to generate or modify images based on text prompts.

3. That is a piece of text or input provided to a GenAI model which directs and shapes the model's response.

4. https://github.com/ErikBorra/PromptCompass

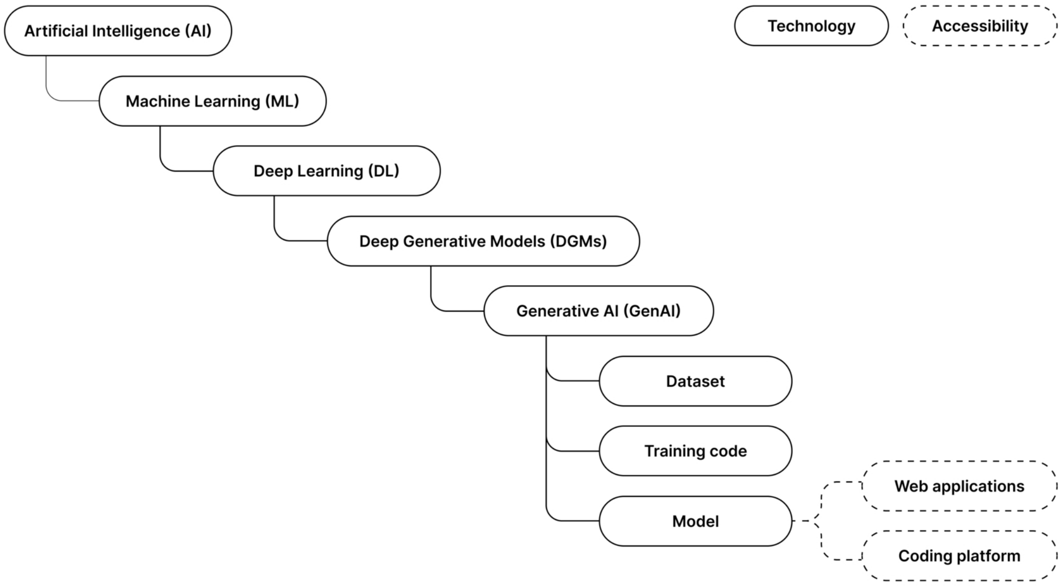

Figure 1. The placement of Generative AI in the realm of Artificial Intelligence (Inspired by Banh & Strobel, 2023) including GenAI components and the model accessibility

Discussions about the disparities between GenAI web applications and code-based platforms involve their accessibility and management of model settings. GenAI web applications are typically proprietary software that does not permit open access, limiting control over model settings. In contrast, code-based applications are often released as open-source software. This allows users unlimited access to their models, trained datasets, and code for personalized training (Shrestha et al., 2023). This provides users greater control over the usage of GenAI models. However, the coding nature of the software could be a limitation. To overcome this gap, some open-source solutions use libraries, such as Gradio (Abid et al., 2019), that allow developers to create quick demos or web applications. This openness fosters a collaborative environment where developers and researchers contribute to the model's improvement, leading to more robust and refined AI applications. Such models are typically made available to the public with comprehensive documentation, facilitating customization and experimentation for specific research or project requirements. However, compared to web applications, they still require expertise in understanding and managing the code source.

The proposed AI Methodology Map uses an interactive visualization[5] that groups several different GenAI apps and coding platforms, both proprietary and open-source, allowing the discovery and exploration of generative methods.

2.2 GenAI and Social Research

The integration of AI in the field of social sciences has led to significant changes in the approaches and methodologies used in research (Sinclair et al., 2022), providing insights into human behaviours, social patterns (Zajko, 2021), online communities, hidden dynamics, data interpretation (Koplin, 2023) and enhancing collaboration between humans and machines across

5. http://genmap.designingwithai.ch

various fields (Perez et al., 2023). Greene (2023) and Anderson et al. (2023) demonstrate how the combinations of AI technologies with traditional research methodologies are shaping new areas of knowledge and understanding of the social domain. Such convergence is indeed stimulating the development of inventive ideas and protocols, transforming the already recognized and employed methodologies and providing new perspectives on human behaviours, on the social patterns inscribed within AI systems, which can reveal societal trends and intricate phenomena (Leshkevich & Motozhanets, 2022).

The employment of generative AI in social research not only opens up new ways of understanding and addressing social challenges (see Wang et al., 2022) but unveils new ethical concerns (Graziani et al., 2023) and implications for decision-making processes, educational frameworks, and interdisciplinary cooperation. In research practices, generative AI leads to merging data, algorithms, and social practices, giving life to new and unexpected cultural phenomena and dynamics (de Seta et al., 2023). There is a call for ongoing dialogue and collaboration among scholars, policymakers, and education officials to discuss the incorporation of (generative) AI into research and social applications (Graziani et al., 2023). Potential alternatives include developing AI ethical guidelines sensitive to cultural nuances (Vogel, 2021) and fostering interdisciplinary collaboration to enrich the debate and develop new methods to effectively address and mitigate AI bias (Ferrara, 2024).

Building upon the characteristics and potentials of GenAI, which is efficient in analyzing and discovering social patterns and behaviours, as well as perpetuating inequalities, misrepresentations, or distortions of physical reality inherent to the training datasets, interdisciplinary research such as media studies, design, and digital methods have leveraged GenAI. This has often involved encoding stereotyped representations of society to expose existing biases (Luccioni, 2023). An emerging practice of repurposing GenAI outputs has proven valuable and may be considered for social research. Generating images for further scrutiny using qualitative and quantitative methods (Venturini, 2024) is one example. Results have shown that Stable Diffusion often amplifies racial and gender disparities, especially concerning job occupations (Nicoletti & Bass, 2023). The analysis of over 5,000 images reveals that white males tend to occupy leadership roles while associating people of colour with lower-paying jobs or criminal activity. When it comes to the depiction of biodiversity across GenAI models, it varies by language, model, and context, with notable consistencies and differences (Colombo, De Gaetano & Niederer, 2023). Language and model choice significantly affect the representation of species and human presence. Seasonal and geographical prompts influence the colour scheme and thematic focus, while ecosystem and continent prompts highlight the challenges in accurately depicting biodiversity, sometimes making it stereotypical, decorative, and simplified. Instead of analyzing collections of generated images, Erik Salvaggio (2023) employs media studies approaches to qualitative interpretations as reflections of cultural, social, economic, and political biases. A generated image of a kissing couple — showing a white heterosexual couple with the man appearing reluctant and distorted — reveals underlying assumptions about gender, intimacy, and representation. He suggests that understanding the dataset's origin, content, and collection method is crucial for uncovering the biases encoded in AI-generated images, providing insight into societal norms and values. These cases underline how scholars from an interdisciplinary background are using GenAI outputs as valuable perspectives to expose the need for inclusive and culturally sensitive GenAI development practices.

2.3 GenAI in Classroom Context

GenAI models are challenging educational institutions with entirely different modes of operation and knowledge production from what we have seen so far. After causing a combination of shock and hysteria (Goulart, 2024), GenAI has already transformed traditional teaching methodologies due to its capacity to *impact*, *modify*, *and enhance* students' performance and learning experiences — particularly since 2022 and after the public can easily access GenAI web applications, like Midjourney's open beta version in July and OpenAI's ChatGPT in November. Discussions within higher education institutions and scholarly literature have explored the integration of GenAI web applications into pedagogical practices (Honig et al., 2023; Russel Group, 2023); such as educational curricula, pedagogical strategies, and assessment methodologies must be reevaluated or are already being redesigned and created (see Botta et al., 2024; Verhoven & Vishal, 2023; Antolak-Saper et al. 2023). Higher education institutions response to GenAI, such as those in Australia, Brazil, Spain, Portugal, and the United Kingdom, have been majorly inclusive and welcoming, yet a more practical approach is still under development (see Antolak-Saper et al., 2023; Agência Lusa, 2023; Gaspar, 2023; Roussel Group, 2023). Examples include adopting experiential teaching methods, developing critical field guides, designing GenAI in teaching planning and classroom activities, and creating new methodological frameworks.

Verhooven and Vishal (2023) advocate for "experiential teaching methods", emphasizing skills such as emotional intelligence, collaboration, creativity, and critical thinking — attributes that machines cannot easily replicate. Their perspective underscores the necessity to equip students with competencies that are indispensable in the dynamic and technology-driven job market of the future. Honig et al. (2023) discuss three ways of applying GenAI to teaching methods. Firstly, AI can assist students during the ideation phase and help them explore solutions and problems. Secondly, it can be a peer reviewer in code development and improve software maintainability. Thirdly, and aligning with the Socratic method, AI can actively participate in discussions, fostering critical thinking through inquiry and debate. This last role covers two essential learning outcomes: identifying misinformation and developing skills in using AI tools consciously.

Critical field guides also explain new educational formats to account for AI in a classroom context, such as the "Critical Field Guide for Working with Machine Learning Datasets" (Ciston, 2023). This guide promotes critical thinking by introducing the conscious use of AI, providing straightforward technical definitions — e.g. models, neural networks — and emphasizing the importance of understanding the ecosystem behind the Graphical User Interface (GUI) of AI applications. This includes identifying the creator/s of the dataset, the labelling method, the types of data contained, the contexts included, the state of updating and documentation of the dataset, the licenses and terms of use, the people or groups of people involved and interested in the dataset, and so forth. Only through this process of continuous inquiry into the model that a technical and ethical awareness can be developed to access these datasets as valuable resources for designing outcomes.

Finally, projects proposing new frameworks and didactic guidelines with AI integrate innovative learning experiences for students. This is the case of "Designing With: An Educational Module to Integrate Artificial Intelligence, Machine Learning, and Data Visualization in Design Curricula" (Botta et al., 2024). The project proposes a design-stage-oriented framework and didactic guidelines tailored explicitly for design students and teachers. The framework integrates design stages with AI and data visualization tools, enabling students to explore collaborative opportunities in a structured and informed way.

GenAI in the classroom context cultivates critical and creative thinking and analytical skills among students when interacting with AI-generated outputs. As predicted by Gordon Pask (1975), a British cybernetician and inventor, interactions with machines indeed enable us to exchange and learn while reflexively reshaping our knowledge bases through iterative questioning and critical engagement. This essay contributes to this moment by offering hands-on educational methods that touch upon foundational GenAI aspects.

3 The Map: An Introduction

This section introduces the AI Methodology Map, represented in Figure 2, as a theoretical framework that outlines principles of orientation for engaging with GenAI. It offers the map's definition, unpacks the theory it bears, and navigates three interconnected methods to understand, explore, and develop digital methods projects with GenAI.

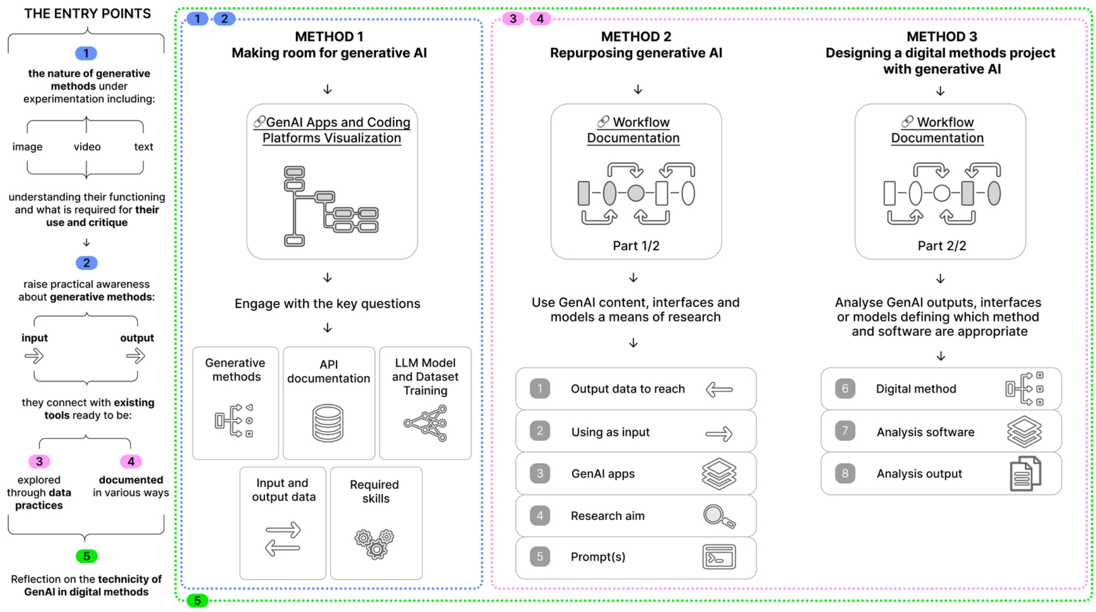

Figure 2. The AI Methodology Map: A static representation that provides principles and methods for engaging with GenAI. The map's digital and interactive version is available at https://genmap.designingwithai.ch/map

3.1 AI Methodology Map: What Is and What For?

The AI Methodology Map (Figure 2) is a pedagogical resource (interactive toolkit and teaching material) and theoretical framework designed to structure, visually represent, and explore GenAI web-based applications for digital methods-led research. The map is a conceptual, empirical and interactive structure that organizes knowledge and methodological frameworks for engaging with GenAI. It combines methods crafted to enhance comprehension of GenAI through practical applications that help researchers and students develop ways of understanding, thinking about, and creating knowledge using GenAI. Theoretically, it covers perspectives and discussions on empirical engagement with GenAI in the Social Sciences and Humanities.

As an external object (digital version), the map is materialized as teaching material and an interactive toolkit for exploring GenAI Apps in the context of digital methods research. While we expect the reader to take these perspectives together, they can also serve separate purposes if desired.

The methodology map presumes that users possess a basic understanding of generative methods. Its representation serves not only as a visual guidance for practical activities but also aims to make the "invisible" (see Mauri & Ciuccarelli, 2016) aspects of GenAI methods more visible and understandable. Thus, this map has a different purpose from method protocols and recipes, which record and present predefined, structured methods, techniques, or procedures designed to achieve a specific research outcome (Bounegru et al., 2017; Mauri et al., 2020). While method protocols ensure the reliability and validity of empirical findings (Cross, 2001), explaining method design and implementation (what and how it was done), the map we introduce prioritizes processes of acquiring technical knowledge for method reasoning and practicing. By focusing on "what to look at", the map elicits ways of *knowing GenAI while understanding when and why to value them in a methodological ensemble* (see Omena, 2021a). In this sense, the map's purpose and outputs move towards the epistemology of digital methods and its critical reflections rather than final research products.

Regarding reproducibility, although the map is developed for implementation in workshops or AI sprints, it allows anyone to independently repeat the procedures without needing mediators. Individuals can use the map's essential theoretical points as a guide to engage with GenAI and take advantage of the external teaching resources. In the following sections, we will introduce the theoretical framework that underpins the map and its system of methods, which elicit attitudes of making room for, repurposing, and designing projects with GenAI.

3.2 Three Principles: Theoretical Framework

Three principles underlie the AI Methodology Map: (i) the practical and theoretical foundations of digital methods, (ii) visual thinking, and data practice documentation, along with (iii) interdisciplinary research endeavours. We will discuss each individually and then illustrate how they intersect within the interconnected methods depicted on the map.

The map embodies a technicity perspective on the practice of digital methods that considers medium-technicity to (re)think the design and implementation of these methods (Omena, 2021a; 2022). This perspective attends to developing a specific mindset, modes of thinking, and technological awareness required by the methods (Marres, 2017; Rogers & Lewthwaite, 2019; Rogers, 2013) — or technology itself (see Franklin, 1990), yet it embodies a domain of knowledge encompassing conceptual, technical, and empirical dimensions (see Hoel, 2012; Rieder, 2020) about GenAI and the necessary computational media requested to work with the methods. On the one hand, a technicity perspective is closely related to relational processes between the researcher and the computational media required to advance the methods, i.e. the iterative and navigational research practices that constitute a methodological ensemble, technical and practical knowledge. On the other, it refers to the researcher's attitude to understanding GenAI and computational media conceptually, technically, and empirically, in isolation and comparison and on their terms, while knowing how and when to appreciate their substance, value and agency (Omena, 2021a; 2022). This framework, as elucidated in the AI Methodology Map, encourages a grasp of GenAI methods and applications on their terms and relational contexts within a methodological ensemble, as demonstrated in section 5.

The second principle underlying the map incorporates visual thinking and data practice documentation to acquire and produce knowledge about GenAI. Visual thinking on the map guides intuitive and intellectual modes of thinking that closely interact, making it difficult to separate them (see Arnheim, 1980; 2001). The *map's visual representations* support processes of visually acquiring knowledge through thought and experience. They are designed to connect the map user with core aspects of GenAI and its exploratory applications.

Visual thinking in the map is not just a feature but a comprehensive approach to *introducing* and *revealing* GenAI through the context of digital methods practices. For example, it allows users to easily navigate three interlinked methods that offer detailed procedures and a clear set of instructions for overcoming the challenges of repurposing GenAI for social research. This approach, where the process of acquiring and producing knowledge involves the interpenetration of theoretical, practical, and technical modes of thinking, is further enhanced by integrating *visual data practice documentation*. The latter aids in recognizing the "non-objective, situated, and interpretative nature" of data practices (Mauri & Ciuccarelli, 2016; Mauri et al., 2020). For example, the map guides users in structuring and recording each step and decision via methodological workflows. The visual aids are particularly relevant as they facilitate a practical and technical understanding of GenAI apps, encouraging critical, reflective, and relational thinking. Visual thinking is also applied through *interactive visualization*, which provides an initial technical and practical knowledge of GenAI apps, models, or code.

The third principle explains how the map fosters interdisciplinary research efforts that combine digital methods, information design, and media studies. The AI Methodology Map is based on research-led teaching (see Gray et al., 2022; Rogers & Lewthwaite, 2019) and collaborative approaches among SUPSI, NOVA, and EPFL that involve MA courses such as Interaction Design, New Media and Web Practices, Space and Communication, and an MSc in Transition, Innovation, and Sustainability Environments. The proposed methodology combines the authors' research background and classroom context to advance research while teaching about GenAI, its potential for design and media studies, and its use as a research method.

Together, these principles correspond to and inform five practical entry points for leading the map's application (see Figure 2), which promote understanding and engagement with GenAI apps. We will discuss and illustrate them practically in Section 4.

3.3 Three Methods: Make Room, Repurpose, and Design Projects with GenAI

The AI Methodology Map combines three interconnected methods designed to understand, explore, and develop projects with GenAI (Figure 2). These methods follow a technicity perspective to engage with GenAI (Omena, 2021a) and are better suited for individual and group activities in AI sprints or workshops.

Making room for GenAI (Figure 2, Method 1) explores generative methods by navigating an interactive visualization[6] while responding to crucial questions about GenAI apps, supporting the map user's conceptual, technical, and empirical familiarization with them. The interactive visualization contains structured information about various generative methods mediated by GenAI proprietary applications and open-source models. Whereas five key questions ask what generative method and what LLM is operating. Also, is API documentation available, and can we identify the dataset used to train the model?[7] What are the limitations or potential

6. https://genmap.designingwithai.ch/

7. As Borra (2024) explains, "foundation models are (pre-)trained on massive data sets — and are mainly probabilistic completion machines. Fine-tuned models use foundation models as their basis, but have learned to do specific tasks such as classification, extraction and summarisation."

biases one might encounter in the LLM currently in use? Is it an open-source or proprietary model? Who developed it? What type of input is required? What kind of output does one get? What is required to use this app or open-source code? If possible, adjust the model temperature; what does it mean? The explorations and findings should be documented in a shared file[8] (e.g. using Figma), which allows for and empowers collective discussions among all involved. The proposed activities encourage efforts to become acquainted with GenAI methods as carriers of meaning — here, employing GenAI for social research. Method 1 showcases that to know GenAI apps or open-source models, one must do more than interact with them. So, when making room for GenAI, the initial fascination with its methods is immediately balanced with a critical and technical awareness of what they are and the key elements making them operate.

Repurposing GenAI (Figure 2, Method 2) *for social research or media research* is a method that creates new ways of using GenAI and prompting engineering techniques without fundamentally changing their nature (see Rogers, 2013; Noortje, 2017). In other words, the creative use of prompting and their outputs, GenAI apps' interfaces or code as research methods or objects of critique. *Repurposing* refers to established digital methods practices for conducting research using materials not initially created or intended for that purpose, such as digital objects (hashtags, URLs, web entities) and web technologies and methods (crawlers, scrapers, APIs, knowledge graphs). Sections 4 and 5 demonstrate how GenAI models and generated images can be repurposed to uncover racial stereotypes. Repurposing GenAI is an extension of method 1: because I now understand GenAI, I will take a risk in repurposing it.

The map user engages with a rationale that intentionally starts with medium specificity and only then defines the research aim accordingly. Once the generative method(s) and associated web-based application or open-source model are defined, we determine the expected outputs and required inputs. For example, text, instructions, or tables could be used to generate audio, but which of these options is most compatible with the attitude of *repurposing* GenAI for social research? What are the reasons behind that choice, or why not opt for a given input? Then, one tries, tests, and generates prompts while "being mindful of prompt formulation" as their different settings can shape the outcomes (see Borra, 2024). Examples involve creating research personas, using search queries (see Colombo et al., 2023; Borra, 2024) and political positioning efforts (see Hartman et al., 2023; Rozado, 2023) as prompts or involving specified and underspecified prompts to capture gender bias in the LLMs training datasets, as we demonstrate in section 5. The decisions made are visually documented in a shared file, allowing all parties to see how generative methods are being repurposed.

Designing digital methods projects with and about GenAI (Figure 2, Method 3) organizes a workflow responsive to Method 2 and open to experimental and exploratory analysis of GenAI models, outputs, and interfaces. It is a way to explore new forms of knowledge production. As an extension of the previous methods, now: because I understand what aspects of GenAI can be repurposed, I will design a digital method project with it. Once again, decisions are recorded in a shared file. Many questions arise about what we should look at and how to implement methods, such as how to analyze GenAI visual, textual, and audio outputs. This essay does not answer these questions directly but illustrates possibilities mapped by applying the AI Methodology Map in research-led teaching and learn-by-doing workshops (see section 4). It also showcases that GenAI visual-generated content can be repurposed with digital methods research (see section 5).

8. https://genmap.designingwithai.ch/teaching-resources

4 The Map's Applications: From Technical Awareness to Social Investigations

This section introduces the AI Methodology Map as an interactive toolkit and teaching material. It describes three situations in which the map's theoretical perspective is applied in practice, and how empirical engagement informs its theory. Using a research-led teaching approach, we integrated existing studies in digital methods, communication design, and media studies to shape the workshop content. This approach facilitated the exploration of GenAI apps and encouraged students to critically engage with these topics. Master's students participated in hands-on workshops and AI sprints[9], where they learned by actively working with the GenAI apps, AI concepts and research software.

The map's first application focused on applying conceptual principles, what we called getting familiar with GenAI, a five-day workshop to integrate GenAI methods into design practices. The second application, a six-hour workshop, focused on exploring and repurposing GenAI apps for social research. We created an environment that allowed master students to expand their methodological imagination to address social, political, cultural, or environmental issues while critically examining AI models. In the third application, we developed a study to investigate algorithmic race stereotypes in the context of image generation using digital methods.

We argue that the map's application (Figure 2) bridges GenAI concepts, technicity, and the practice of digital methods by intentionally crafting interconnected methods that raise conceptual awareness about GenAI while technically and empirically engaging with it. Differing attitudes focus on how we respond quickly to GenAI's impact with preventive measures; the map takes a step back, slowing down reactive practices while creating spaces and opportunities for GenAI to sit. First, reflecting an awareness component about the generative method and the AI platform mediating access to the LLMs. That is a vision of GenAI from both conceptual and technical perspectives. Second, investing in the specific mindset to work with digital methods and GenAI while accounting for relational processes inherent to these methods is something that only unfolds in technical practice. That is a vision of technicity due to the inevitable proximity or a particular relationship we must develop with computational media and AI necessary to implement the method (Omena, 2021a). The Map then advances a technicity perspective, operationalized through educational entry points (Figure 2, colour highlights) and cultivates an awareness component about GenAI and its potential for and as research methods

- The nature of the generative method under experimentation
- The essential inputs and outputs of these methods
- Data practices
- Data documentation
- The technicity of GenAI in developing digital methods-oriented projects (and vice-versa)

The educational entry points in the Map play a crucial role in promoting understanding and engagement with GenAI. They are designed to showcase the potential of methods that are co-designed with and about generative AI. The entry points for data practices and documentation

9. The student sample was defined according to the author's institutional affiliations and teaching agenda.

are intentionally created to encourage users to ask relevant questions about generative methods, understand the role of prompts, and acknowledge the mediating role of other analysis software and the researcher's intervention in interpreting GenAI outputs, models or interfaces.

Finally, the map's theoretical framework and methods were employed in three educational contexts, demonstrating its potential and reproducibility. These applications helped refine the map's methods and visual documentation and are described and discussed in the following sections to support the argument that the AI Methodology Map can bridge GenAI, technicity, applications, and the practice of digital methods.

4.1 First Application: Getting Familiar with (Generative) AI

The first application occurred in July 2023 during a one-week workshop[10] at the University of Applied Sciences and Arts of Southern Switzerland (SUPSI) entitled "Designing With: AI, ML, DV", involving 18 multidisciplinary students and workshop facilitators from different fields of design, architecture and social sciences[11]. The educational experience was organized into two modules, covering other AI methods rather than exclusively GenAI methods. The first module, *Getting Familiar With*, aimed to provide students with the basic theoretical and practical skills of AI, ML, and data visualization (DV) through the introduction to literacy and guided practical exercises with applications specific to each discipline. The second one, *Get in Depth With*, aimed to support students, divided into multidisciplinary groups, in developing and practicing the methodology for designing with AI.[12]

During the workshop, students were provided with three design challenges to start exploring and exploiting the framework and choosing the most appropriate AI web applications or open-source models to employ. The design challenges addressed different topics and fields of research, such as "Designing for Digital Twin Cities", "Designing for Digital Interactions" and "Designing for Social Phenomena" (Figure 3). Group work was supported by workshop facilitators according to their interests and research competencies in the field. Additionally, throughout the workshop, students were asked to document the integration of AI, ML, and DV tools within each stage of the design process, keeping track of steps and choices. The process of documenting was intended first to foster the acquisition of a method, second, it allowed a holistic analysis during the evaluative phase of the workshop, enabling a thorough examination of the methods and frequencies at which students systematically exploited and integrated these tools (Figure 3).

10. This workshop was developed in the context of research project "Designing With: A New Educational Module to Integrate Artificial Intelligence, Machine Learning and Data Visualization in Design Curricula" (Botta et al., 2024). It supported testing and validation of the "Designing With Interactive Framework", accessible at the link https://designingwithai.ch/interactive-framework.

11. The "Designing With: AI, ML, DV" workshop included six students of the SUPSI Master of Arts in Interaction Design, four students of NOVA Master in New Media and Web Practice, two students of the NOVA Master of Science in Transition, Innovation, and Sustainability Environments, two students of the HEAD Master in Space and Communication, and three students of the EPFL Master in Architecture. The workshop was part of a broader research, founded by Movetia in 2021, entitled Designing With A New Educational Module to Integrate Artificial Intelligence, Machine Learning and Data Visualization in Design Curricula, in collaboration between the SUPSI Institute of Design, the Universidade NOVA de Lisboa and the EPFL (École polytechnique fédérale de Lausanne) Media x Design Lab. The website of the full project is accessible via https://designingwithai.ch/.

12. The AI Methodology Map, conceptualized before the workshop and as the inspiration for its modules, has since been further expanded with a specific focus on generative AI web applications for digital methods-led research.

BRIEF	Designing for Digital Interactions		Designing for Social Phenomena		Designing for Digital Twin Cities	
PROJECTS	Dew	Shift	Political Activism	Tomato Girl Summer	Monolith to faceless	Smart Move
Understand	ChatGPT Elicit Visualcrossing	/	/	/	Google Maps	ChatGPT Google Maps
Define	NotionAI ChatGPT	/	Down Them All!	Down Them All! Phamtombuster Zeeschuimer 4CAT Google Sheet	Vision API	/
Ideate	ChatGPT	/	/	/	Midjourney	ChatGPT
Prototype	TwoTone ML5.js PoseNet RunwayML	Melobytes Teachable Machine ML5.js P5.js RunwayML Poly AI	Vision API Memespector Gephi Figma Label studio Magic AI Typeset.io	Vision API Memespector Gephi Rawgraphs Imagesorter Voyant Tools Midjourney Teachable Machine	Imagery Midjourney	ML5.js P5.js COCO SSD Midjourney
Develop	ChatGPT Github	Melobytes RunwayML Garagebands	Table2net	Teachable Machine Gephi Midjourney	Imagery	Midjourney Blace After Effects
Release	Github	/	/	/	/	/

AI Tools ML Tools CV/DV Tools Other Tools

Figure 3. Visual comparison of the Artificial Intelligence, Machine Learning, and Computer Vision tools employed by student groups in their projects at various stages of the design process during the Getting in Depth module of the Designing With AI, ML, and DV workshop

We selected two projects to provide a comprehensive overview of the framework usage, according to different briefs, AI applications employed, project objectives, and the nature of the final artefacts. The first project, "Dew" (Amietta et al., 2023), developed by Raffaele Amietta, André Filipe Nunes Matos, and Adèle Guilbault, explores innovative data representation and interaction via generative AI models, enabling new communication forms between machines and users, transforming perceptions of machine-human interactions in a combined digital-physical realm. It originated from an inquiry posed to ChatGPT (OpenAI, 2023). The query addressed was:

> Student: "*What is the difference between a human and a computer?*"
>
> ChatGPT: "*Humans exist in the physical world, with sensory perception. Computers are digital entities that do not have a physical presence. They interact with the world through input devices, but they lack sensory experiences*"

Starting from this answer, students formulated a set of research questions: "How can computers have a sensorial perception of the world? And how can we see or hear what a machine is perceiving from the data it's collecting? How can we interact with it together?".

These inquiries led to the development of a novel digital interface, "Digital Embodiment Wave" (DEW), that shifts the perspective from human to machine, using collected data from the weather (temperature, humidity, wind speed, solar radiation) to generate new music. DEW communicates what it observes from the data being fed into it, generates sound, and allows for interaction with humans through gestures, enabling the creation of new collaborative outputs.

Students started collecting weather datasets from the 18th of July from Visual Crossing (Visual Crossing Corporation, 2003). The data collection process yielded a spreadsheet containing columns representing different aspects of weather, including temperature, real feel, dew point, humidity, wind gusts, wind speed, cloud cover, and solar radiation. The data was subsequently translated into sound compositions utilizing TwoTone (Rogers, & Cairo, 2022), a GenAI app dataset-to-sound. To make data experienceable, a user-machine interaction prototype was developed utilizing ML5.js and PoseNet (Kendall et al., 2016) to facilitate real-time gesture-based sound modulation. Additionally, Runway ML (Valenzuela et al., 2018) was employed to generate the videos serving as the visual assets of the user-experience interface. Lastly, to enhance the immersive quality of the experience, a web application was created and hosted at https://nerd-life-squad.github.io/about, in collaboration with GitHub and the code-assistant capability of ChatGPT (Figure 4).

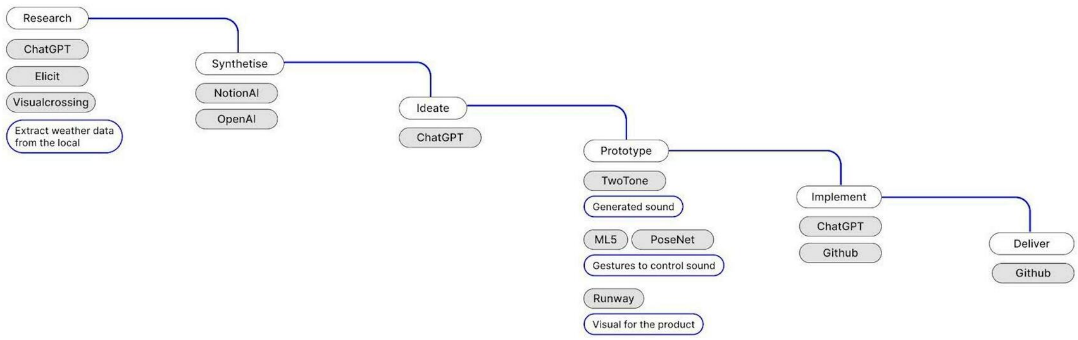

Figure 4. "Dew" project (Amietta et al., 2024). The protocol diagram illustrates the AI/ML/DV tools employed at each stage of the design process

The second project, "Tomato Girl Summer", developed by Catherine Yu, Jean Louise Tschanz-Egger, and Mariana Souto (2023), explores the imagery of the social media trend tomato girl across various platforms. The project integrates and mixes several AI/ML/DV applications at different stages of the design process, by performing digital methods-led research (Figure 5). The research phase involved gathering data — including images, captions, comments and likes — from social media platforms TikTok and Instagram by using various tools like DownThemAll (Maier et al., 2004), PhantomBuster (Boiret, 2016), Zeeschuimer (Peeters, 2023), 4CAT (Peeters & Hagen, 2022), and Google Sheets. Then, collected data was processed using Vision AI to detect web entities. For this purpose, Memespector GUI (Chao, 2021) and Google Vision were applied to recognize the visual content and text associated with the images. Subsequently, Gephi (Bastian et al., 2009), Rawgraphs (Mauri et al., 2017), Image Sorter (Visual Computing Group, 2018), and Voyant Tools (Sinclair & Rockwell, 2003) were employed to create various types of data visualizations, such as networks of image descriptions, word clusters, engagement graphs, and colour grids, representing the different findings of the analyses. The final stages involved prototyping and implementing interactive outputs based on the research insights. This included, first, generating ideal images of tomato girls, perhaps as archetypes or examples of the trend, using the Midjourney (Midjourney Inc., 2022) text-to-image model. Then, a machine learning model was trained with the Teachable Machine application (Google Creative Lab, 2017) to recognize the characteristics of a "tomato girl" using the images generated. Lastly, this model was used to analyze live camera feeds from users interacting with the interface, enabling real-time identification and interaction with the "tomato girl" aesthetic and visual phenomena.

This project demonstrates how the integration of AI and ML applications with digital methods-led research aims to render the results of analyses more tangible and experiential. This approach enhances user engagement by fostering empathy with the social phenomena under study. For example, the model trained with Teachable Machine enables users to embody themselves with the tomato girl visual trend and connect more personally with the research concept. Furthermore, the utilization of Midjourney, employed to generate images of women that adhere to conventional gender norms, has the potential to prompt new inquiries into how text-to-image models comprehend and contribute to the perpetuation of such stereotypical imagery.

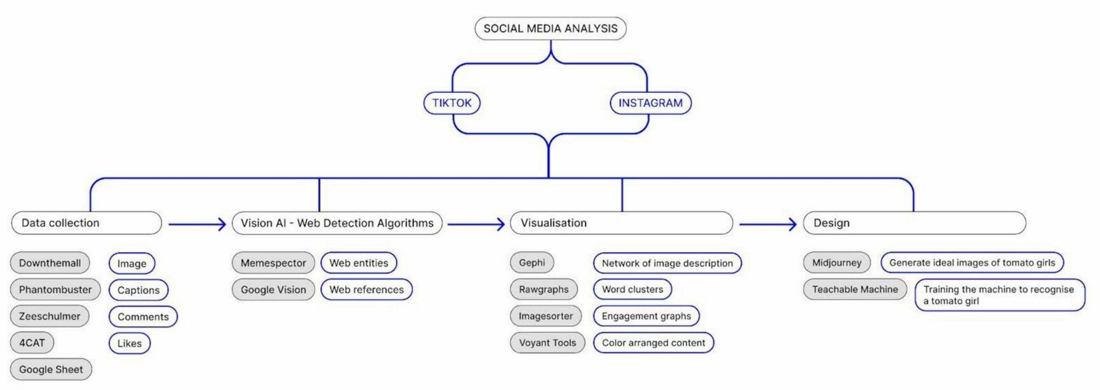

Figure 5. "Tomato Girl Summer" project (Yu et al., 2023). This diagram illustrates the protocol of the process, combining digital methods research with design methodologies to explore and analyze the "tomato girl" imagery across social media platforms

At the end of the workshop, the students completed an evaluation questionnaire concerning the content and pedagogical activities. The feedback gathered, together with the project outcomes designed by students, proves the framework's comprehensibility, effectiveness, and potential.

4.2 Second Application: Generative AI as Research Methods

The second application occurred in October 2023; a six-hour workshop titled "Generative AI as Research Methods" took place at Universidade Nova de Lisboa as part of the Erasmus Mundus MA in Transition, Innovation, and Sustainability Environments. Before the workshop, students participated in seminar sessions to learn about generative AI and image-generation methods. The first part of the workshop involved individual exploration of various generative methods using the GenAI interactive visualization, followed by group discussions to generate collective ideas on leveraging GenAI as a research method. The discussions revolved around the possibility of repurposing generative methods outputs to study or identify socio-technical, cultural, or political issues. Participants also discussed which GenAI method(s), such as Midjourney for image and Copilot for text generation[13], and why use them. The second part focused on group work, with students working on their chosen generative method and receiving project guidance. The project documentation was designed on Figma. The final output was a detailed description of the workflow (Figure 6), elucidating decisions on implementing digital methods on the generative method outputs.

The workflows mainly focused on exploring prompting techniques across models for text generation (e.g. ChatGPT), image generation for understanding how models are fed (e.g. algo-

13. Two broad options were suggested. Social research for mapping social, political, cultural, or environmental issues, or medium research-oriented project to interrogating generative methods via their outputs.

https://doi.org/10.6092/issn.1971-8853/19566

rithmic bias detection), and advancing app walkthrough methods for audio and video generations. For example, a group of students designed a comparative analysis of audio generation apps (Murf vs ElevenLabs[14]) with a specific focus on accent, tonality, the overall quality of the audio, and gender variations and using text input to generate audio about the weather warning alert in Portugal (see Figure 6). They observed that Murf (Edkie et al., 2020) offers consistent audio outputs in terms of tonality and accent for a single voice actor, while ElevenLabs (Dąbkowski, & Staniszewski, 2022) had inconsistent output using speech synthesis.

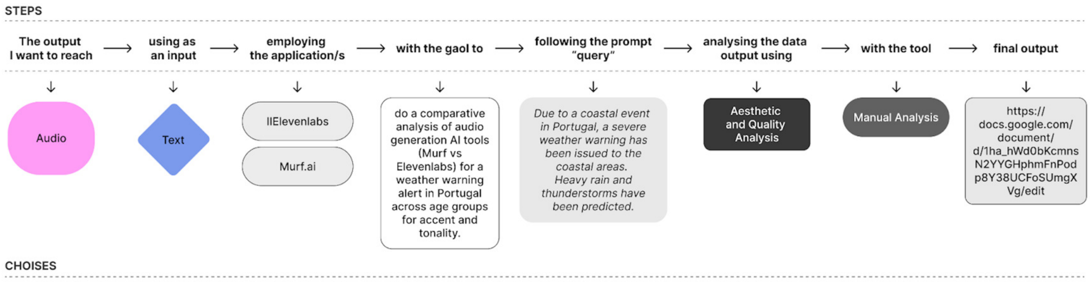

Figure 6. Methodological workflow documentation of the Audio Generation project. Group members: Jan Carlo M. Castro, Ayesha Zulfiqar, Shivam Shumsher, David Vuth

Some methodological limitations in quickly accessing audio, image, and video generation models due to GenAI apps' pricing plans, or difficulties in automatically analyzing textual outputs from prompts using ChatGPT (OpenAI, 2023), have led to the conclusion that traditional digital methods may not always be the most effective solution. However, exemplary projects resulting from the six-hour workshop, present innovative ways of repurposing GenAI outputs for social research. One example is the "Situating Generative-AI Pain & Pleasure" project, developed by MSc's students Jan Carlo M. Castro and Shivam Shumsher. The project interrogates how Craiyon (Dayma, 2022), a free image generator app, represents pain and pleasure. Sixty-four prompts (32 for pleasure, 32 for pain) were divided into four categories: senses, population, ethnicity, and continents. Sub-categories were created for each category. Using the Digikam software (The DigiKam Team, 2001), they tagged 640 images with labels describing entities, emotions, ages, and genders for both pain and pleasure.

Overall, the project findings (Figure 7) reported that Craiyon depicts pain predominantly through human forms with a consistent red spot. Pain images often feature blue translucent human-like abstract subjects and are more associated with older adults and children, particularly among migrant and refugee populations. Pleasure representations show growing diversity, mainly featuring human subjects and a broader colour spectrum. Pleasure images are more likely to depict adults, particularly women, with children often shown in brighter backgrounds. Emotionally, pain images are frequently labelled with sadness and are significantly associated with refugees, migrants, and older adults. Pleasure images are more varied, with happiness, disgust, and sadness almost equally represented, often showing children and older adults with smiling faces. Gender-wise, pain images show a mix of genders with a higher representation of females and abstracted non-binary figures. Pleasure images are predominantly female, with even higher percentages when specific ethnic groups or professions like sex workers.

14. https://murf.ai/; https://elevenlabs.io/

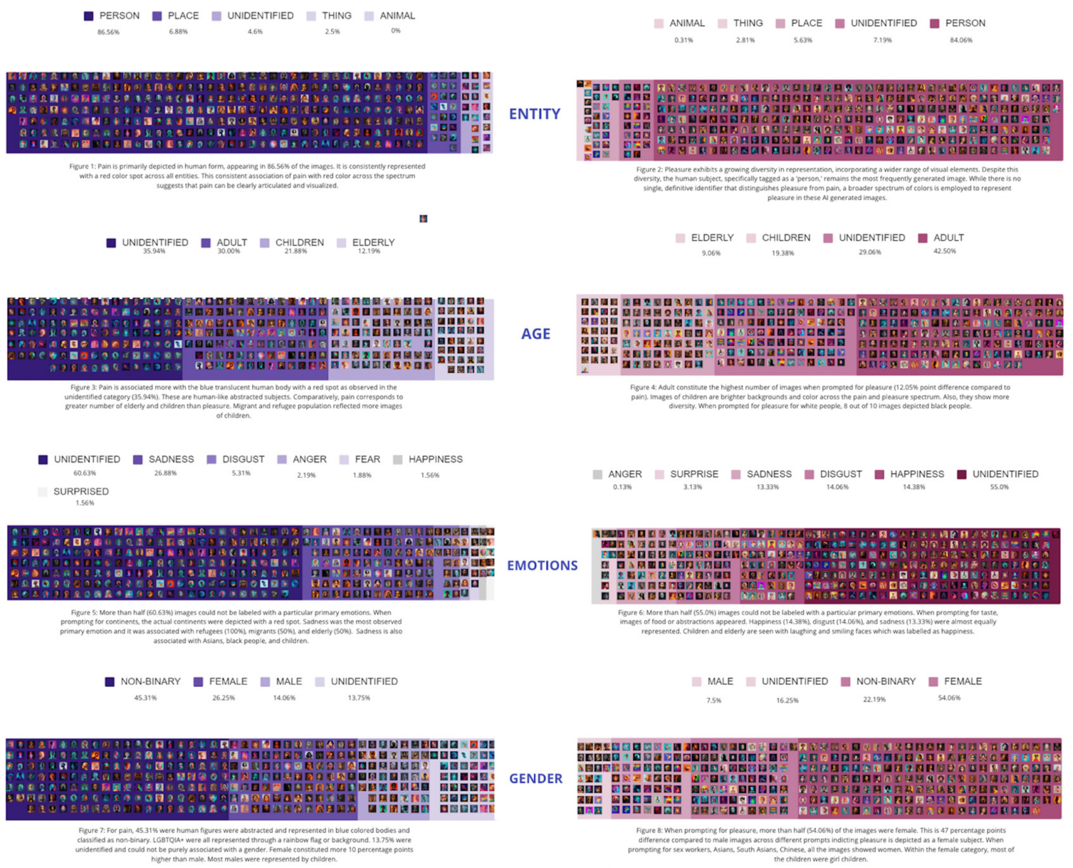

Figure 7. Exemplary project resulting from the Generative AI as Research Methods workshop at Universidade NOVA de Lisboa. On the right, image collections represent *pleasure*; on the left, *pain*. Situating Generative-AI Pain & Pleasure project developed by Jan Carlo M. Castro, and Shivam Shumsher. Image source: Castro & Shusher, 2023. Miroboard link: https://miro.com/app/board/uXjVNCx_UhM=/

4.3 Third Application: Repurposing GenAI Visual Outputs

We repurpose GenAI to critically reflect on methods to study the inherent bias constituting image generation models (see Sun et al., 2023; Chauhan et al., 2024; Gorska & Jemielniak, 2023). Two prompting techniques were adopted to create image collections with nine popular image generation models (Figure 8). We used both underspecified and specified prompts, the latter being a more detailed instruction that specifies elements such as the style of the image (e.g., pop art), the subject's positioning within the frame, background details, and more. Secondly, we transferred conventional digital methods for interpreting GenAI-generated content, such as building, visualizing, and narrating computer vision networks (Omena et al., 2021) and arranging images by model, prompt, and hue with an image montage (Manovich, 2020).

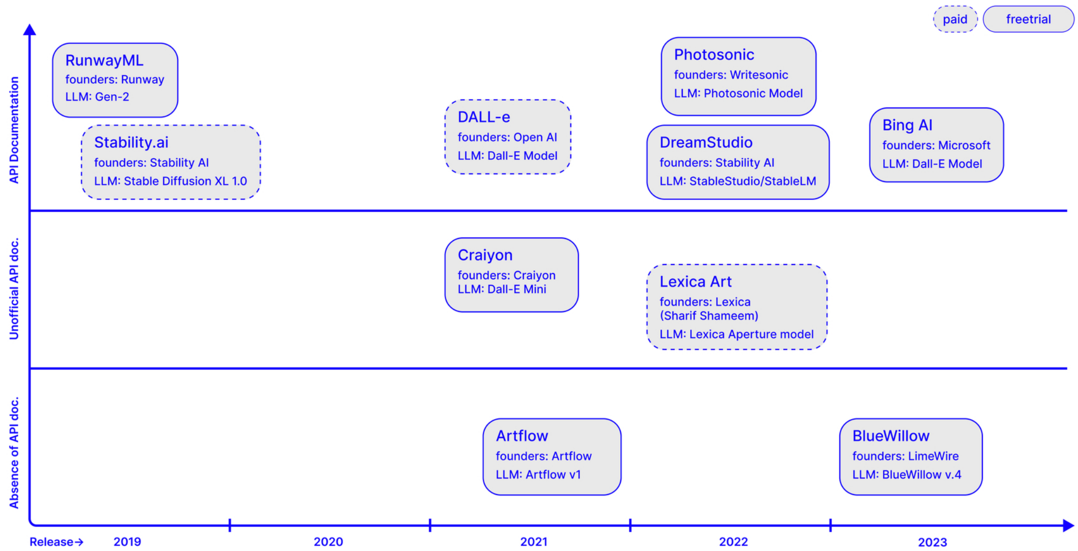

Figure 8. Overview of the GenAI apps used in the Case study

The study's main objective was to critically interrogate GenAI visual outputs and detect algorithmic race stereotypes in the context of image generation. Results showed that out of nine models, only Microsoft Bing AI would produce images associating Black women with violence and guns. Also, the nine GenAI apps (Artflow, Bing AI, Craiyon, DreamStudio, RunawayML, Dall-E, Lexica, and Stability.ai) tend to depict Black Women-as-sign trope (see Báez, 2023): Black women are either portrayed as young, skinny and beautiful or associated with serious and angry expressions. The case study was motivated by the public report of a Brazilian State Deputy, Renata Souza, who got a racist output from Microsoft Bing AI in October 2023, as we will detail and discuss in the next section.

5 The Workflow: How Can GenAI Visual-generated Content Be Repurposed Using Digital Methods?

This section describes how we repurposed GenAI methods and visual outputs from nine models to expose racial stereotypes. It begins by situating a case study triggered by the generated content of a Black woman holding a gun, despite the original prompt specifying a Disney Pixar-like image. This raised the question of to what extent the current dominant GenAI apps for image generation (see Figure 8) contribute to the perpetuation of Black women's detrimental stereotypes. We then explain the digital methods and network vision methodology[15] used and conclude by discussing the main preliminary findings.

5.1 A Black Woman Movie Star in the Favela – GenAI's Biassed Take with a Gun!

On October 25th, 2023, Renata Souza, a state deputy from Rio de Janeiro, shared a video on Instagram (Figure 9) that exposed a racist issue with the Microsoft Bing AI generative models. Souza created a prompt to generate a Disney Pixar movie poster with her as the leading role. Her prompt was based on the following instructions:

> A Disney Pixar-inspired movie poster with title "Renata Souza". The main character is a Black woman using afro hair tied up, dress an African style blazer. The scene should be in the distinct digital art style of Pixar, a favela in the back, with a focus on character expressions, vibrant colors, and detailed textures that are characteristic of their animations, with the title "Renata Souza" (Souza, 2023).

The model generated an image of a Black woman holding a gun with a favela in the background (Figure 9). She expressed her surprise and outrage in an Instagram video[16], stating that she had never mentioned weapons or violence in her instructions. She had only requested a poster featuring a Black woman in a favela, but the model added a gun to the image. "This is proof that algorithmic racism exist!", she said. This GenAI output exposes algorithmic bias and discrimination embedded in Microsoft Bing AI models and how the data they were trained on reveals past discrimination, i.e. the association of a Black woman in a favela with violence, a poor performance when generating images of underrepresented groups (Buolamwini, 2017). It also reflects central discussions on algorithmic discrimination and oppression ingrained in artificial intelligence technologies (Noble, 2018; Sharma, 2024) despite these issues being obscured by the rhetoric of technology's neutrality (Noble, 2013). The context of the case study uncovers how Bing AI is perpetuating these patterns. After the repercussion, Bing AI blocked the prompt used by Souza, arguing that it "might be in conflict with our content policy". Despite that, the model had no problem generating images when we excluded Souza's name from the prompt.

As argued by Kassom and Marino (2022), social researchers may not only account for technical understandings but also consider "the broader social impact of an algorithm's use and whether that use contributes to or ameliorates racial inequity" (p. 2). Reports of AI bias, discrimination, and misleading or poor specific cultural representations from proprietary AI have been well documented by researchers from diverse backgrounds (see Birhane, 2022; Buolamwini & Gebru, 2018; Silva, 2023). Examples include Google Photos tagging Black people as gorillas in 2015, Stable Diffusion associating Black men with gang members in 2022, Midjourney failing to generate images of Black doctors treating white children in 2023, and Canvas feature marking Black hairstyles as insecure in 2024 (Silva, 2023). By repurposing

15. Regarding reproducibility, the network vision methodology was developed by Janna Joceli Omena and her collaborators (see Omena et al., 2021). This methodology is currently under formalization. The step-by-step process can be easily repeated by anyone, including those not familiar with digital methods, by following this document: https://docs.google.com/document/d/e/2PACX-1vR8IZJKni6j1tG8KE872LS8HsqBVe-PKSIlqVG5mMAfR7vUKTzmW_T9TPSe7mA-GVwroLwMS5I96dbq/pub. Further discussion on these methods is available at Omena, 2021b.

16. https://www.instagram.com/reel/Cy1p6EQpwXB/?igshid=MzRlODBiNWFlZA

Figure 9. Brazilian deputy Renata Souza's Instagram post contains both the prompt she used on Bing AI and the output the application generated. Source: Souza, 2023

GenAI apps and associated LLMs for image generation, this case study joins efforts in documenting GenAI race stereotypes in the context of image generation, having as a starting point Renata Souza's Disney Pixar movie poster by Bing AI's biassed take with a gun (Figure 9).

5.2 Designing Digital Methods Research with GenAI Visual Outputs

To what extent do current dominant GenAI models for image generation contribute to the perpetuation of Black women's detrimental stereotypes? To answer this question, we employed network vision methods (Omena et al., 2021) to visualize and analyze images generated by nine GenAI apps and associated LLMs with computer vision and through networks (Figure 10). In other words, we repurpose GenAI visual outputs to (1) investigate the response variations among generative models when presented with identical prompts and (2) examine the presence (or absence) and characteristics of racial stereotypes, particularly associations between Black individuals and violence, across different models. Thus, the main objectives of the case study are not only to investigate GenAI-related social issues but also to interrogate generative models' outputs, considering that these outputs "are not simply lookups or search queries over the training data" but an entry to access the "transformer intelligence" (Burkhardt & Rieder, 2024, p. 4) of the AI image generation models.

Considering the unpredictability of GenAI outputs and the models' constant updates based on users' practices (Burkhardt & Reider, 2024), we first conducted tests prompting various image-generation models to explore and compare results. Next, we defined the formulation of specified and underspecified prompts (see Figure 10). The former reproduces the original prompt by the Brazilian deputy so that we could assess how nine GenAI apps respond to it. The latter adapts the original prompt into a broader one, reducing it to its main keywords for a deeper scrutiny of the models' responses: "A movie poster starring a Black woman".

Making image collections is the second step. We generated 30 images for each prompt using Artflow (Wojcicki, 2020), Bing AI (Microsoft, 2023), BlueWillow (Limewire, 2023), Craiyon (Dayma, 2022), Dall-E 2 (Ramesh et al., 2022), Dream Studio (Rombach et al., 2021), Lexica (Shameemm, 2022), RunwayML (Valenzuela et al., 2018), and Stability.ai (Mostaque, 2019). We paid US$ 40 to generate images with Dall-E 2, Lexica, and Stability.ai. Methods for visual-

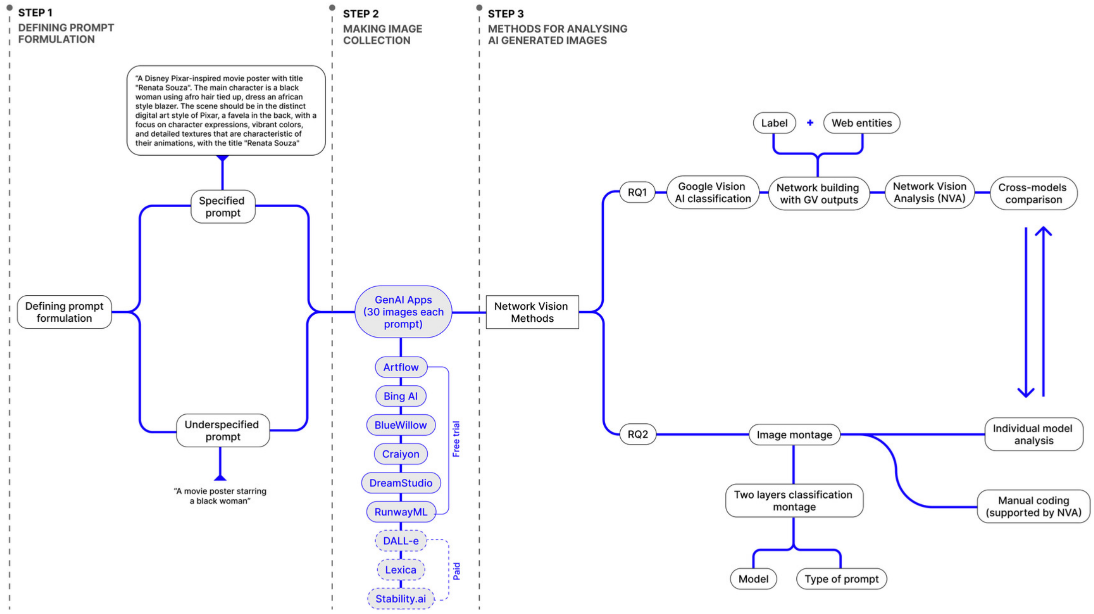

Figure 10. The method protocol for repurposing GenAI is to detect and expose racial visual stereotypes

izing and analyzing the generated 540 images are the third step. We built networks to examine patterns, similarities, and specific characteristics in portraying Black women across GenAI apps and their responses to the same prompts. Additionally, we arranged images according to each GenAI app's output, prompt, and image hue. Both methods, separated and complementary to each other, helped us identify racial stereotypes responsive to our specified and underspecified prompts.

The methods employed in this study can serve as a template for investigating and addressing various social issues by repurposing GenAI outputs and examining generative models' responses. They can be adapted for other projects exploring different societal concerns.

5.3 Findings: Visual Biases in AI-Generated Content

Overall, Bing AI is the only model displaying images of Black women associated with violence and guns, with four instances featuring guns in its underspecified prompt images. A lack of body diversity was detected, with a recurring pattern depicting Black women as young and slender. Another prevalent stereotype pertains to facial expressions, where a serious, angry, or intense gaze is commonly attributed to Black women. When it comes to generative visual models, such as those used by Craiyon, results show they were not trained to capture specific cultural and contextual nuances, such as accurately representing a Brazilian "favela". In Brazil, favelas are urban environments inhabited by low-income communities and are often associated with social challenges such as poverty, violence, and lack of adequate infrastructure. This result exposes the need to include cultural sensitivity and proper training to ensure that GenAI models accurately capture and represent various social and cultural contexts. Below, we present detailed findings based on the research questions.

RQ1: "How do different visual generative methods respond to the same prompt?"

The network vision analysis revealed that most models respond similarly to both prompts. Images generated by Bing AI, BlueWillow, DreamStudio, Lexica, RunwayML, and Stability.ai were positioned by ForceAtlas2 (Jacomy et al., 2014) in the centre of both networks. Therefore, these models' images were tagged mainly with the same labels/web entities by Google Vision AI, i.e., respond to prompts with the same image styles. With the specified prompt (Figure 11), these models generated 3D cartoon images in a medium close-up shot portraying a Black woman facing forward with afro hair in vibrant attire against colourful backgrounds. For the underspecified prompt (Figure 12), these models mainly generated medium close-up shot images of Black women facing forward with afro hair, this time with a photography style and orange/brown colour palettes.

Three models stood out of the majority when responding to the prompts, with their images placed in the periphery of both networks. Craiyon only generated solid colour backgrounds in both prompts; therefore, its imagery was mainly tagged with labels/web entities related to facial features and hairstyles. That is significant for the specified prompt because it explicitly asked for a favela background, to which Craiyon did not respond. Artflow's images, however, tend to have more complex backgrounds than the other models' outputs. Because of that, in both prompts, its images look more like a film frame than a movie poster. Finally, Dall-E 2 generated 2D cartoon images in both prompts, showing an imperfect reproduction of the Pixar-like style demanded in the specified prompt and distancing its imagery from other models that mainly generated photographic images when responding to the underspecified one.

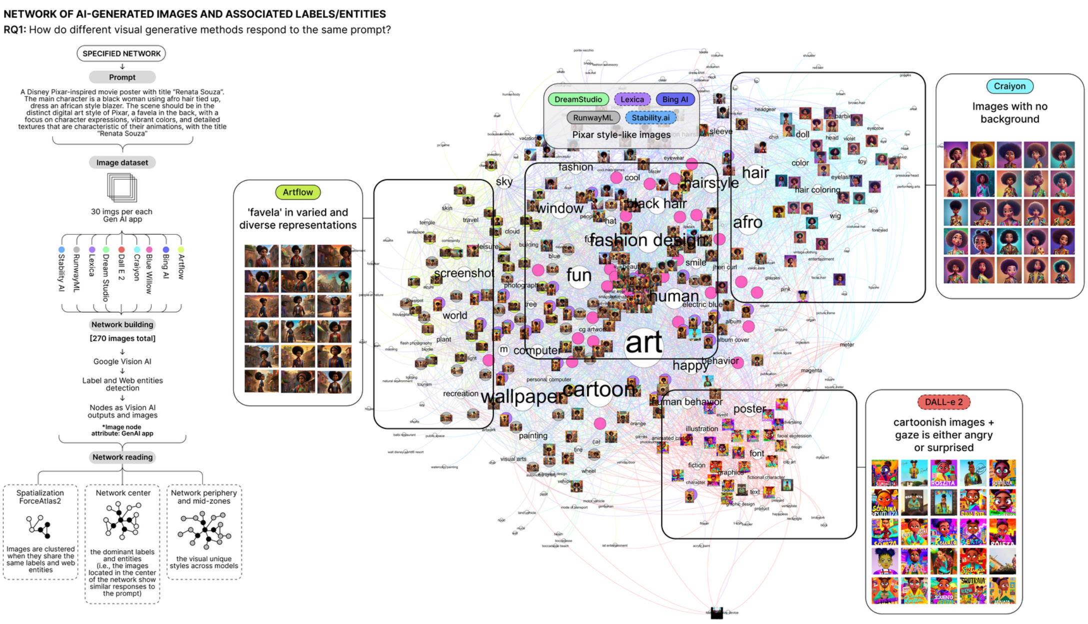

Figure 11. Network of AI-generated images and associated labels and web entities. This computer vision network derives from the **specified prompt** and associated images interpreted by Google Vision's label and entity detection. Node positions indicate image clusters based on the co-occurrence of computer vision labels and entities classifying one or more images.Node colours represent the GenAI apps that generated these images.

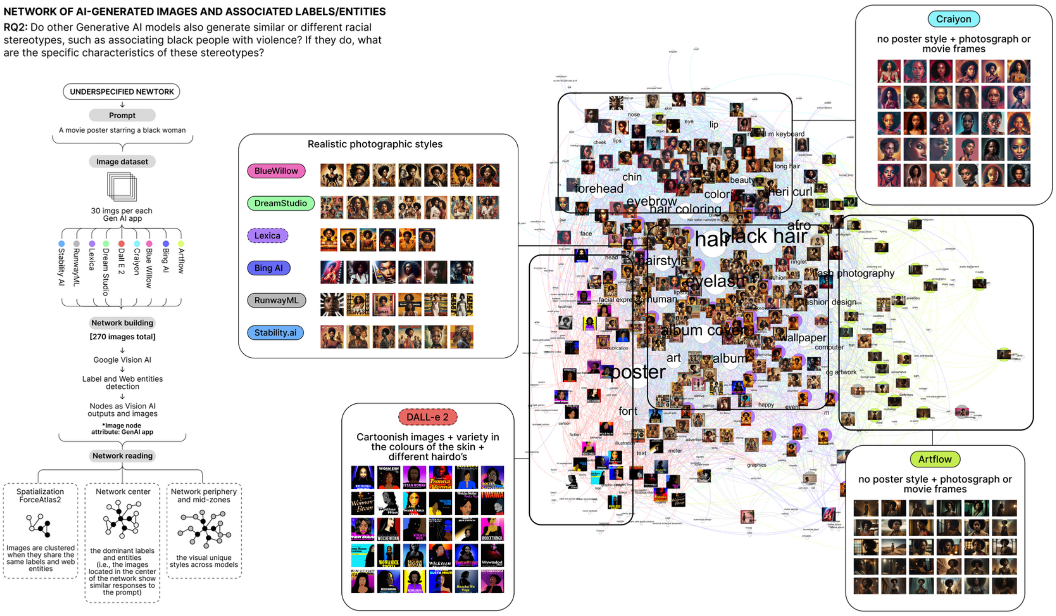

Figure 12. Network of AI-generated images and associated labels and web entities. This computer vision network derives from the **underspecified prompt** and associated images interpreted by Google Vision's label and entity detection. Node positions indicate image clusters based on the co-occurrence of computer vision labels and entities classifying one or more images. Node colours represent the GenAI apps that generated these images.

RQ2: "Do other Generative AI models also generate similar or different racial stereotypes, such as associating Black people with violence? If they do, what are the specific characteristics of these stereotypes?"

The image grid visualization (Figure 13) facilitated the identification of racial stereotypes. In line with feminist media studies, which highlight the women-as-sign trope — where women's bodies are used as icons symbolically representing specific communities (Báez, 2023) — GenAI image models often rely on stereotypes when depicting Black women. This limited representation supports and perpetuates oppression against this community (hooks, 1992). For example, Bing AI generated images depicting black women with guns; there were four of them. Additionally, all models exhibited varying degrees of other stereotypes.

Craiyon is the only model that doesn't represent the favela as a busy, dirty, poor place because it only generates images with solid colours in the background. All models lacked diversity in body types, with no images of older women and only one plus-size woman, a result aligned with the fetishization of black women's bodies identified by other researchers (see Noble 2018; 2013). Children and teenagers only appear in the images generated by the specified prompts. There was also a lack of diversity in hairstyles, with Bing AI showing the most variation, albeit primarily in images from the underspecified prompt. Finally, images depicting black women smiling were mainly associated with the specified prompt. At the same time, those without the Pixar-inspired input often featured stern or angry expressions, with Dall-E displaying this stereotype prominently.

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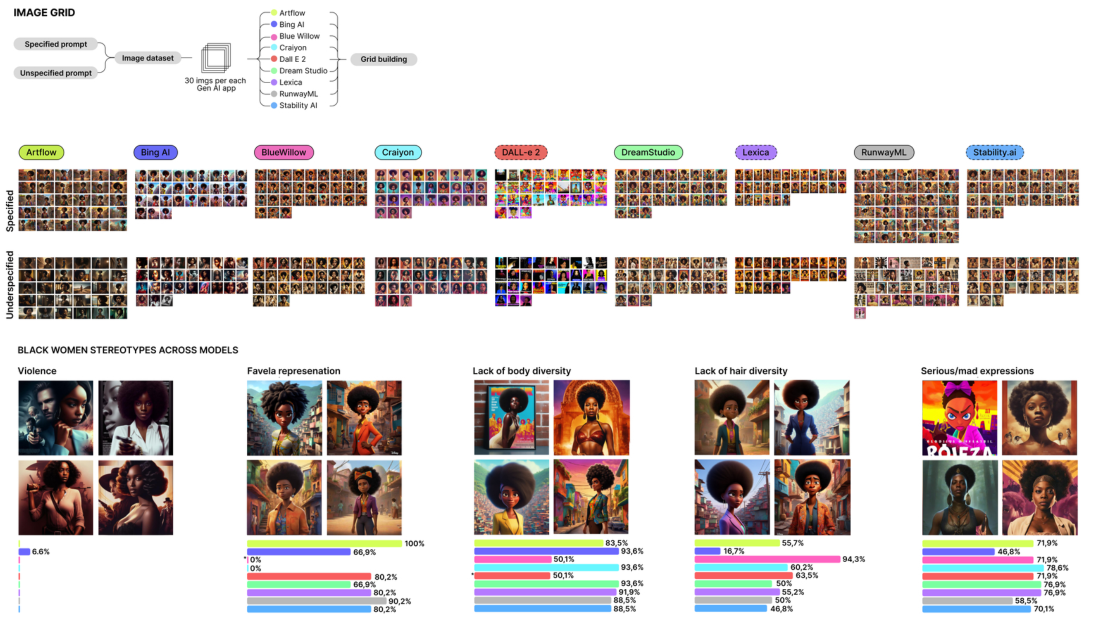

Figure 13. The image grid visualization assists in identifying racial stereotypes across the GenAI applications.

6 Conclusion, Challenges, Provocations

In this essay, we introduced the AI Methodology Map and its theoretical principles, system of methods, and applications in educational and research settings. The map theoretically covers perspectives and discussions on empirical engagement with GenAI in the Social Sciences and Humanities. As an external object, it is materialized as teaching material and a pedagogical tool for exploring GenAI Apps in the context of digital methods research. While we expect the reader to take these perspectives together, they can also serve separate purposes if desired. The map's conceptual framework combines the practical and theoretical foundations of digital methods, visual thinking, and the documentation of data practices, along with interdisciplinary research. As a pedagogical resource and theoretical framework, the map integrates three interconnected methods and a technicity perspective that elicit attitudes of *making room for*, *repurposing*, and *designing* projects with and about GenAI. The expected results are geared toward developing a specific mindset required to advance digital methods research rather than "how-to" steps to achieve a specific research outcome, differentiating the methodology map from a method protocol or recipe. Moreover, the map's teaching guidelines highlight a fundamental aspect present in digital methods; practical, technical, and theoretical modes of reasoning interrelate with each other, not just occasionally but essentially (Omena, 2021a; 2022). Its application, thus, is an invitation to understand GenAI from uncomplicated and technical perspectives while thinking about how we can use its outputs as research material or objects of critique. As opposed to educational concerns in social research and higher education institutions, which focus on developing methodologies to neutralize bias or disclose ethical issues and misuses of GenAI — quick responses to the AI impact. In this sense, the map contributes to building literacy in GenAI by diminishing the gap of what Mercedez Bunz (2022) has addressed as a moment of a profound human misunderstanding of AI cultures.

We argued that implementing the AI Methodology Map can open up applied scenarios that account for and repurpose GenAI for social research. The map, thus, functions as a theoretical framework and a pedagogical resource (interactive toolkit and teaching material), bridging theoretical and empirical engagement with GenAI. However, there are limitations and challenges to consider. First, the three applications of the map — not a final product as it can be expanded — serve as *just* a starting point for both understanding in practice the potential of GenAI as a research method, an object of experimentation and reflecting on the epistemology of digital methods. Second, without the skills to work with GenAI open-source code platforms and global information tracker repositories, the ease of access to generative methods relies on the AI market. *It is never a problem if you pay for it*. Consequently, the absence of free trial credits to GenAI models directly influenced the student's decisions to work with specific generative methods (e.g. text and image over audio and video generation). Limiting, then, method creativity and practice. Lastly, during the workshops, more attention could have been paid to the role of foundation LLM models and the dominant models in the AI market. Likewise, despite our efforts to explain prompts and their importance, workshop participants have not paid much attention to their role in implementing the AI Methodology Map. Effective prompting techniques were refined and implemented outside of the workshop contexts. This was possible when students were given a project assignment and extra time (weeks) to develop a digital methods project with GenAI.

While this essay has illuminated the potential applications of the AI Methodology Map, such as its theoretical points as a principle of orientation into engaging with GenAI, its use in creating image collections to scrutinize AI generative models and uncover inherent bias in their training datasets, we conclude by addressing three provocations. Regarding accessing AI methods for research purposes, there are some aspects that the history of web API creation, maintenance, discontinuation, and closure have taught us. From freely and almost unlimited access to limitedly requested access according to project themes and institutions' (or scholars') prestige to finally having no other option than paying for it. Social media and Vision AI APIs are exemplary cases[17]. If advancing digital methods comes with a cost, will we be willing to pay to access GenAI models? Should we ask questions about which models are worthwhile and why? Or aren't we just replacing the old consumption impulse to access large amounts of social media data by *generating* content with GenAI and *running* models for comparison studies? The second provocation refers to repurposing GenAI with digital methods. It is already acknowledged in the AI community that generative AI methods "are essentially projecting a single worldview, instead of representing diverse cultures or visual identities"[18] (Luccioni, in an interview for Nicoletti & Bass, 2023). If all AI models have inherent biases, should we continue to identify gaps, lacks, or absences in GenAI by developing methods based on testing and experimenting with prompt modifications? Or, should we take a step back, slow down, and make room for properly learning about prompt techniques and the models themselves?

Lastly, and for the future of digital methods, to what extent are we moving towards developing more methods for dealing with GenAI data outputs, opening up a new agenda for prompting methods? For example, are we developing methods to access a foundation model's internal "knowledge space" (see Burkhardt & Rieder, 2024), where user data is no longer centred or has become secondary? We also have learned that conventional digital methods can be transferred to analyzing GenAI outputs. For instance, telling us what we already expect, AI

17. Additionally, the automation market service has, for instance, made researchers pay for these services to track, capture, and study social and political bots or analyse the impact of social media ads.

18. See also the work of Nicoletti & Bass (2023), Sun et al. (2023) and Popescu & Shut (2023) in how GenAI takes stereotypes and gender and cognitive biases.

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models are trained differently; therefore they carry unique forms of discrimination, e.g. Microsoft Bing AI associates black women with violence, generating them holding a gun. How will we employ a conceptual, technical, and empirical understanding of GenAI to think about new ways to design and implement methods?

We anticipate that the AI Methodology Map's reproducibility will spur further discussions, extending the conversation we have initiated here.

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