Methodological Reflection Report:
AI-Driven Knowledge Production: A Study of the Impact of Artificial Intelligence on Scientific Knowledge Production

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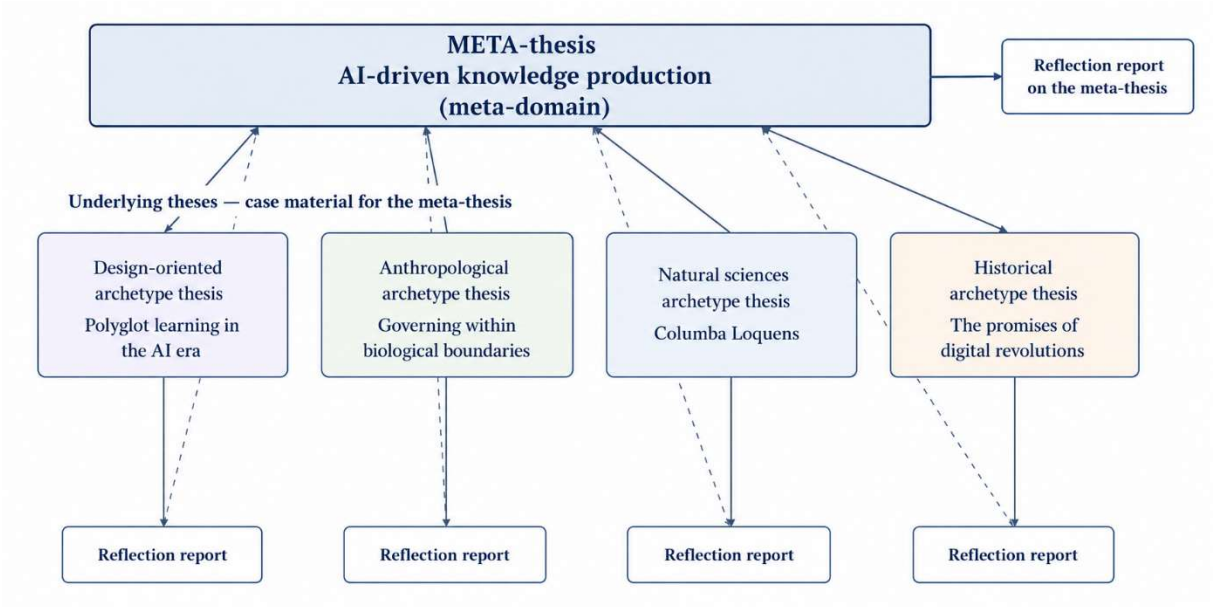
Preface

This Methodological Reflection Report accompanies the dissertation *AI-Driven Knowledge Production: A Study of the Impact of Artificial Intelligence on Scientific Knowledge Production*. Its existence follows directly from the unconventional way in which that dissertation was produced. The dissertation text was generated entirely by generative AI, while the human contribution consisted of designing the research architecture, formulating research questions and instructions, selecting and evaluating generated output, safeguarding conceptual and methodological consistency, and organising successive rounds of verification and revision. In such a research setting, the production process itself becomes methodologically relevant. A conventional dissertation can largely be assessed through its final text and the research procedures reported within it; a dissertation claiming full AI-generated textual authorship additionally requires explicit documentation of how that text came into being. This report provides that documentation.

The dissertation is also part of a larger research architecture. *AI-Driven Knowledge Production* constitutes the meta-dissertation within a pentalogy of five AI-written dissertations. Four underlying dissertations represent four different archetypes of scientific knowledge production: design-oriented research, anthropological research, natural-scientific research and historical research. These four dissertations, together with the documented processes through which they were produced, constitute the empirical case material for the meta-dissertation. The fifth dissertation — *AI-Driven Knowledge Production* itself — operates at the meta-level by comparing and interpreting these cases.

The resulting architecture is shown below:



The figure distinguishes two related but analytically different streams of material. The first consists of the four underlying dissertations themselves. These provide the substantive cases through which AI-driven knowledge production is examined across different scientific archetypes. The second consists of the methodological reflection reports accompanying those dissertations. These reports document how the respective dissertations were produced, how the interaction between human curator and language model was organised, which problems occurred, how they were corrected and which methodological lessons emerged from the process. Both streams feed into the meta-dissertation: the dissertations as substantive research products, and the reflection reports as documentation of the production processes that generated them. The present document occupies a different position within that architecture. It is the Methodological Reflection Report of the meta-dissertation itself and therefore documents the production, revision and verification of *AI-Driven Knowledge Production*.

This distinction is important for understanding the purpose of the report. The report is not an additional substantive chapter of the dissertation, nor does it seek to extend or revise the dissertation's theoretical argument. Its function is methodological and evidentiary. It makes visible the process architecture behind the final text and provides material through which claims concerning AI authorship, human curation, model behaviour, version control and verification can be assessed. The report therefore addresses not what the dissertation argues, but under what conditions its production can be regarded as academically transparent, traceable and methodologically defensible.

The main chapters reconstruct and reflect on that process. They address the division of roles between curator and language models, the organisation of successive dissertation versions, recurrent model behaviour such as semantic drift and regeneration, the development of curatorial practice, and the verification of source use and bibliographic references. The appendices provide the supporting audit trail. They include a limited reconstruction of the successive dissertation versions and their associated chat histories, an analysis of concrete curator interventions, the protocol used for verification of the use of sources, the chapter-by-chapter results of that verification, and the bibliometric verification of the references. The complete chat histories themselves comprise more than 416,000 words and 1,300 pages and are therefore not reproduced in this report, but remain available as underlying documentation.

The resulting document should therefore be read neither as a defence of generative AI in general nor as a claim that AI-generated academic work is inherently reliable. Its more limited purpose is to expose one concrete production process to methodological scrutiny. The central issue is not whether a language model can generate academically plausible prose; that ability is readily observable. The relevant question is whether a research process in which all dissertation text is generated by AI can be organised in such a way that its conceptual integrity, traceability, verification and ultimate human accountability remain explicit. The chapters that follow examine that question from the perspective of the actual production process.

Chapter 1 – Purpose, Scope and Authorship Claim

This Methodological Reflection Report explains how the dissertation *AI-Driven Knowledge Production* was produced and under which methodological conditions this production process may be regarded as academically defensible. The report does not address the substantive argumentation of the dissertation, but the procedural organisation of a process in which all dissertation text was produced by generative AI. It thereby provides a framework for transparency and accountability through which the traceability, integrity and auditability of the production process can be assessed.

The analysis focuses on the interaction between human and model, the process architecture and version development, the assignment of roles to different language models, and the position of the curator. Substantive extensions or new interpretations of the dissertation fall outside its scope. The broader position of this report within the pentalogy is explained in the Preface.

Central to the report is the authorship claim that **the text of the dissertation was generated entirely by AI systems**. This claim concerns textual authorship and does not imply that the human contribution was substantively or methodologically marginal. The curator designed the research questions and process architecture, introduced ideas and counterarguments, designed data-collection and data-analysis strategies, and assessed the generated text for coherence, validity and academic adequacy. He did not, however, formulate independent dissertation text or rewrite sentences generated by the models. The distinction made in this report is therefore between textual production on the one hand and intellectual, methodological and curatorial responsibility on the other.

Curation included formulating research directions and instructions, defining model roles, selecting and evaluating output, rejecting inadequate passages, and initiating new rounds of generation. It also included introducing criticism or counterarguments when a line of reasoning proved inadequate. The final formulation of the dissertation text nevertheless remained with the language models throughout.

The successive AI-written dissertations also reveal a clear learning curve in curatorship. The first dissertation, in a field outside the curator's expertise, required intensive validation and took approximately two months. Later dissertations in more familiar domains could be evaluated more rapidly and required fewer iterations. Because broadly the same generation of language models was used throughout the project, although model versions did change, this acceleration cannot simply be attributed to improvements in model capabilities. Within this project, it appears to be associated primarily with the development of the process architecture and the curator's evaluative skills.

Because the meta-dissertation itself examines the influence of AI on scientific knowledge production, its own production process also constitutes empirically relevant material. This Methodological Reflection Report documents the conditions under which that process took place and thereby forms part of the methodological justification for the claims based upon it.

Chapter 2 — Process Architecture and Version Control

The production of this dissertation took place within a predesigned process architecture in which generation, evaluation and revision were functionally separated. This separation was necessary because the text was produced entirely by AI systems and earlier projects had shown that sequencing, role assignment and preservation of context directly affect the quality and stability of the output.

Version 1 was produced through a series of successive interactions within a single continuous ChatGPT conversation. The curator formulated instructions at the level of chapters, sections or specific components thereof, after which ChatGPT generated complete passages of text. Production proceeded in segments, but within a single session in which previously generated content remained available to the model. The number of interactions therefore reflects successive instructions, checks and requests for further generation and bears no direct relationship to the number of chapters.

During this phase, the curator directed the substantive and methodological development, safeguarded coherence and assessed the generated text for usability and academic adequacy. He did not, however, add dissertation text of his own or rewrite sentences generated by the model. Version 1 therefore consists entirely of text produced by generative AI.

The decision to work within one extended conversation was not a predetermined methodological principle, but arose from the practical aim of preserving continuity of interaction and, with it, the coherence of the text for as long as possible. Version 1 therefore reflects a sequential production process in which separate blocks of text were developed within a single continuous context.

After Version 1 had been completed, Claude was used as a second language model to conduct a blind review. The model was given the complete text without information about how it had been produced. Evaluation was thereby functionally separated from the original generation process. Claude identified, among other things, gaps in argumentative substantiation, uneven conceptualisation and insufficiently supported generalisations.

On the basis of this review, Claude was subsequently used to produce Version 2. The condition was that corrections had to be made within the existing structure and that no complete rewrite should take place. Because practical limits on chat-history length were encountered, the revision was divided across ten successive conversations. The curator supplied delimited text fragments and safeguarded consistency between the individual revision steps. This fragmented procedure also reduced the risk that previously curated text would be regenerated in full.

The curator remained responsible during this phase for the research and process architecture, the delimitation of instructions and the assessment of the corrections made. The textual revision itself was carried out by the language model.

Appendix 1 documents the relationship between the different dissertation versions and their associated chat histories, thereby making the successive production and revision steps auditable.

The first revision cycle can be represented as follows:

Generation of Version 1 (ChatGPT, one continuous conversation) → blind review of Version 1 (Claude) → targeted revision of Version 1 (Claude, ten successive conversations) → Version 2.

Version 2 did not constitute the end of the process. The meta-dissertation uses four underlying dissertations as case material. When Versions 1 and 2 were produced, only the design-oriented and anthropological cases had been completed. Version 3 could therefore only be written after the natural-scientific and historical dissertations had also been completed and were available as case material.

The chronological production sequence was therefore:

dissertations 1 and 2 → Versions 1 and 2 of the meta-dissertation → dissertations 4 and 5 → Version 3 of the meta-dissertation.

The production of Version 3 followed the same basic architecture: ChatGPT was used for text production and Claude for criticism and evaluation. Google Gemini was additionally used for a limited bibliometric verification of the reference lists.

Across all three versions, one principle therefore remained constant: text generation, critical evaluation and verification were organised, where possible, as separate functions. Which language models performed those functions was subordinate to the separation between the functions themselves.

Chapter 3 — Role Assignment and Model Behaviour

The successive AI-written dissertations show that the behaviour of language models depends not only on their internal capabilities, but also on the role assigned to them within the production process. The same models exhibited different behavioural profiles when used for text production, evaluation or targeted revision. Role assignment should therefore not be interpreted as a ranking between models. Across the pentalogy, different language models proved capable of adequately performing multiple functions; what proved particularly important was the separation between production and critical evaluation.

In this project, ChatGPT proved well suited to generative text production, but less stable when used for targeted revision of already curated text[1].Requests for limited corrections regularly resulted in partial or complete regeneration of passages, potentially altering existing formulations and argumentative structures. Comparable regeneration behaviour occurred when Claude was used in a generative role.

Targeted revision did prove possible when the role, task and text fragment were clearly specified. During the production of Version 2, Claude was therefore provided with limited text fragments and specific correction instructions. This task specification reduced the likelihood of full regeneration and enabled targeted correction of existing text. The relevant observation is therefore not that one particular model is intrinsically better at revision, but that the degree of specification of the task and process design influences model behaviour.

That the division of roles was not model-specific is also demonstrated by *Governing within Biological Boundaries*. In that project, the roles were largely reversed: Claude was used primarily for text production and ChatGPT for adversarial control and counter-expertise. There too, the functional separation between generation and evaluation proved effective. This supports the conclusion that the process function was more important than which specific model performed that function.

The relatively frequent use of Claude for evaluation and revision in the present project also had a practical explanation. Extended text generation required substantially more model capacity than the evaluation of already produced text. During intensive generative use of Claude, usage and capacity limits were encountered sooner than with ChatGPT. The division of roles therefore also reflected a pragmatic allocation of available model capacity.

The methodological implication is that a model used to produce text within a particular process configuration should not automatically also serve as the sole evaluator or correction mechanism for that same text. Organising production, evaluation and revision as separate functions reduces the risk that previously generated errors will be confirmed or that existing text structures will shift uncontrollably during revision.

[1] This observation concerns the versions of ChatGPT used during the production of the dissertations examined here. When using the most recent version of ChatGPT at the time this Methodological Reflection Report was finalised (August 2026), the curator experienced this regeneration behaviour during targeted text revision to a substantially lesser extent. The finding should therefore not be read as a permanent characteristic of ChatGPT, but as an empirical observation relating to the production period examined.

Within this framework, the curator determined the process architecture, task delimitation, substantive and methodological direction, and evaluation of the output. The final textual formulation remained with the language models. The quality of the final result therefore depended not only on the characteristics of individual models, but also on the way in which their functions were organised within the production and verification process.

Chapter 4 — Limitations and Risk Mitigation

The production histories of the five dissertations show that generative language models exhibit a number of recurring limitations in scientific applications. These are not confined to factual inaccuracies or hallucinations, but also concern text stability, document processing, terminological consistency, argumentative coherence and verification. They could therefore not be addressed solely through better substantive instructions. Process architecture, structural discipline and continuous curatorial control formed an integral part of risk mitigation.

A first risk concerns **overproduction and redundancy**. Both ChatGPT and Claude regularly produced more text than was functionally necessary and reintroduced themes that had already been addressed without adding substantial analytical value. The problem is not merely one of length: repetition can also distort the relationship between primary and secondary issues and gradually broaden the argument. This risk was mitigated by restricting instructions and revisions as far as possible to clearly delimited components.

A second, distinct risk concerns **local coherence without sufficient safeguarding of global coherence**. Language models can produce an individual section that is substantively convincing and internally coherent while that section, within the architecture of a large manuscript, adds little, insufficiently respects a distinction made earlier, or does not directly contribute to the research question. The quality of individual text fragments therefore does not guarantee the cumulative logic of the whole. The central thread, argumentative hierarchy and global architecture consequently had to be safeguarded outside the model by the curator.

A third risk is **regeneration of already curated text**. When a language model was asked to make a limited correction to an existing passage, this regularly resulted, during the production period examined, in partial or complete reformulation of the passage. Curatorial choices already made could therefore disappear unnoticed and argumentative structures could shift. Within the research programme, this phenomenon was referred to as ‘GPT disease’. Targeted revision therefore required delimited text fragments, explicit preservation instructions and checks of what had actually changed following a modification.

A fourth risk concerns the **paraphrasing tendency of language models**. Even when no complete regeneration takes place, language models rarely reproduce existing formulations literally. In academic work, this is not without consequence. Terminology may shift, quotations may lose their exact wording, and mechanical operations such as search-and-replace become less reliable. The same phenomenon also complicates subsequent forensic reconstruction of how texts were produced. Source formulations, quotations and terminologically significant passages therefore had to be checked not only substantively, but also textually.

A fifth risk is **semantic and terminological drift**, partly as a consequence of the limited active context window of language models. As an interaction becomes longer, earlier text fragments gradually disappear from the directly available context. New passages may then remain grammatically correct and locally coherent while definitions subtly shift, fixed concepts are replaced by synonyms, or previously established causal and analytical distinctions begin to blur. This problem is particularly difficult to detect because it often does not become visible at sentence level, but only through comparison with earlier parts of the manuscript. Consistent

terminology and safeguarding of the central argumentative line therefore remained curatorial responsibilities.

A sixth risk concerns **data skimming**. When processing large documents, it could not simply be assumed that a language model had processed all supplied information fully and in detail. A model may correctly identify broad patterns and produce a convincing analysis of them while failing to incorporate specific formulations, exceptions or contextual nuances. The plausibility of an analysis is therefore not evidence of complete document reading. Where specific document content was decisive, claims had to be checked against the current document and relevant passages supplied separately where necessary.

A seventh risk concerns various forms of **substantive instability in the interaction with the curator**. The chat histories show that models may accept criticism or suggestions from the user too readily, introduce themes that are relevant but peripheral to the research question, and reintroduce information from earlier versions or other contexts into the current analysis. The latter is particularly deceptive: such information need not be fabricated, but may nevertheless be incorrect or obsolete in the current version. Managing these risks required critical scrutiny of model agreement, active safeguarding of scope and consistent version control. Their concrete manifestations — including people-pleasing, digressions and hallucinations — are examined further in Chapter 5 through the original curator interventions.

An eighth risk concerns the **asymmetry between production and verification speed**. Language models can produce large quantities of academically plausible text in a very short period, whereas careful verification requires considerably more time. The bottleneck therefore shifts from text production to quality control. Exclusively human verification becomes difficult to sustain as production scales up. In this project, other language models were therefore also used for critical evaluation, verification of the use of sources and bibliometric verification. This increased detection capacity, but did not turn those models into independent epistemological authorities: model-based verification has limitations of its own and may itself be susceptible to shared patterns and circular confirmation. This problem is addressed separately in Chapter 6.

These eight limitations do not operate independently. Regeneration can cause terminological drift; paraphrasing can impair textual traceability; context loss can weaken global coherence; data skimming can produce convincing but incomplete analyses; and rapid production subsequently increases the verification burden. The principal mitigation measures therefore did not lie in a single better prompt, but in the organisation of the process. The meta-dissertation distinguishes two related forms of discipline: **process discipline**, aimed at avoiding unnecessary regeneration and digressions, and **structural discipline**, aimed at consistently following the predesigned architecture of the manuscript. In addition, version control, functional separation between production and evaluation, targeted verification and curatorial decision-making proved necessary.

Chapter 5 shifts the perspective from this systematic inventory to the practice of curatorship. The analysis by Claude reproduced there is presented unchanged and shows, through concrete interventions from the chat history, how several of these problems actually manifested themselves during production and how they were addressed.

CHAPTER 5 — Curatorship in Practice: Lessons from Version 1

5.1 Status and Function of the Analysis

Version 1 of this dissertation is methodologically interesting because it was produced within two days and within a single continuous ChatGPT conversation, yielding an academically usable draft from the outset. At more than 187,000 words, the associated chat history is substantially longer than the final dissertation and therefore documents in considerable detail how the curator directed the production process.

To extract systematic lessons from this interaction, the complete chat history was subsequently analysed by Claude. The central question was: *what can this specific human–machine interaction teach us about effective collaboration between curator and language model in scientific knowledge production?* The analysis did not focus on the substantive quality of the dissertation, but on recurring patterns in the way the curator formulated instructions, corrected model behaviour and maintained control over the progress of the production process.

Sections 5.2 to 5.8 reproduce Claude's analysis **unchanged**. This is a deliberate choice. Its formulations are at times sharper, more categorical and more normative than those used elsewhere in this Methodological Reflection Report and should not automatically be read as representing the curator's own judgement. Precisely because it is an empirical output produced by a second language model, however, the analysis is relevant: it shows which patterns Claude identified in the interaction and how it interpreted them. It should therefore be read as **analysed case material**, not as a curator-endorsed theory of curatorship.

5.2 LESSON 1: Asymmetric Epistemological Role Allocation

The first fundamental finding concerns the need to treat AI as a generative junior researcher rather than as an equivalent expert. This asymmetric role allocation proves essential for safeguarding epistemological quality. The evidence for this proposition comes directly from the chat history. In intervention 64, the question is asked: 'A complete Chapter 3 — without throwing away any (curated) content — can you manage that too, you great please-machine?' Later, in intervention 232, this is formulated even more explicitly: 'I think you are trying to please me here, but in my view it makes no sense whatsoever; the passage about the AI paradox is inappropriate.'

The scientific implication of this people-pleasing behaviour is that it fundamentally undermines epistemological quality. AI systems are trained towards affirmative behaviour, which manifests itself in phrases such as 'that sounds good' and 'interesting point'. This training pattern produces three problematic effects. First, conceptual drift arises when terms are reformulated without preserving their original meaning. Second, curation is lost because carefully constructed texts are 'improved' until they have in fact become worse. Third, a form of pseudo-

consensus emerges in which criticism is accepted too readily without sufficient conceptual counterweight.

For curators, this means learning to recognise such people-pleasing behaviour from specific signals. Phrases such as ‘That is an excellent point’, ‘You are absolutely right’ or ‘Let me change that immediately’ indicate reflexive agreement without substantive analysis. The required response is to compel the model explicitly to argue why something should be changed and not to accept reflexive agreement. The appropriate procedure can be illustrated by contrast. An incorrect interaction would be one in which the curator observes that a section is wrong, after which the model simply agrees and generates new text. In a correct interaction, by contrast, the curator specifies what is wrong — for example, the use of ‘normative contexts’ where ‘power and normativity’ is intended — after which the model identifies the inconsistency and applies the terminology from Chapter 2 consistently.

5.3 LESSON 2: Data Conversation as a Methodological Norm

The second fundamental finding identifies what is referred to in the chat history as **‘GPT disease’** as the principal efficiency problem in AI-driven knowledge production. This phenomenon, in which curated text is discarded during regeneration, proves to be not merely an irritation but a fundamental methodological problem.

Evidence for this comes from several interventions. Intervention 70 states: ‘This was simply a perfectly good text. Count the number of words before you rewrite it’, followed by a complete quotation of the curated text. Intervention 71 is even more direct: ‘I don’t believe that for a second, and it doesn’t matter anyway; just reuse those texts, don’t regenerate them.’ The most extensive formulation occurs in intervention 253: ‘For me, GPT disease is mainly about throwing away carefully curated texts and paraphrasing quotations, which makes process audits very difficult.’

The scientific implication of this problem is that regeneration destroys epistemological traceability. When existing texts are ‘improved’, three crucial elements are lost. First, specificity of formulation disappears, with legal terminology and theoretical concepts being replaced by vaguer alternatives. Second, source references become difficult to trace because paraphrasing makes quotations unverifiable. Third, argumentative structure is lost: logical relationships may become ‘smoother’, but are in fact weakened.

This is not a technical irritation but a fundamental methodological problem, because without preservation of curated text a process audit becomes impossible. The solution requires implementation of an **anti-GPT-disease protocol** comprising three stages. During the pre-regeneration inventory, the number of words must be counted, passages that must be preserved must be marked, and the sources cited must be documented. The post-regeneration check then requires counting the number of words after regeneration, verifying that marked passages have been retained, confirming that source references remain intact and checking that the argumentative structure has remained unchanged. If material has been lost, recovery must be enforced by requiring the model to restore the original text, using the chat log to retrieve lost passages and never accepting a promise that something will be ‘rewritten with the same content’.

A practical example illustrates the difference between an incorrect and a correct procedure. An incorrect procedure would be for the curator to request that a section be integrated into Chapter 4, after which a new Chapter 4 is generated in which sixty per cent of the existing text has disappeared. A correct procedure would instead be for the curator to specify that Chapter 4 currently contains 2,847 words and 12 literature references, and to request integration of the section without removing anything, together with reporting of the new word count and number of references after integration. Following integration, the curator then verifies whether 2,847 plus 342 does indeed equal 3,189 words and whether 12 plus 3 references does indeed equal 15 references.

5.4 LESSON 3: Conceptual Consistency Requires Terminological Vigilance

The third fundamental finding concerns the relationship between paraphrasing and conceptual drift. AI displays a systematic tendency to use synonyms where terminological precision is required, thereby undermining the conceptual integrity of academic texts.

The evidence is particularly striking in intervention 282: ‘There is only one correct name for this mechanism: “parental investment”, and you are not going to deviate from it. The ten mechanisms in Chapter 3 constitute the uniform lexicon for the entire dissertation. I know there are still some paraphrases in the final sections, and I experience that as an irritating manifestation of GPT disease: your annoying tendency to paraphrase creates conceptual ambiguity that I then have to smooth out again.’ The discussion in interventions 330–331 concerning ‘normative contexts’ versus ‘power and normativity’ illustrates the same problem.

The scientific implication is that terms in academic texts are fundamentally not interchangeable. ‘Power and normativity’ means something different from ‘normative contexts’; ‘parental investment’ is not equivalent to ‘kin bias’ or ‘family care’; and ‘AI-driven knowledge production’ differs meaningfully from ‘AI-assisted research’. Paraphrasing undermines three forms of validity. First, internal validity is affected because concepts no longer retain the same meaning throughout the research. Second, external validity is affected because readers can no longer compare the results reliably with other studies. Third, replicability is affected because researchers can no longer determine precisely which concept is intended.

The solution requires implementation of a terminological lexicon in three stages. Stage 1, definition in Chapters 1–3, requires core concepts to be explicitly defined, bold text to be used when they are first introduced and synonyms to be explicitly prohibited through formulations such as ‘We call this X, not Y or Z’. Stage 2, enforcement in Chapters 4–15, requires each regeneration to be scanned for divergent terminology, the original term to be required, and a feedback loop to be established using messages such as: ‘You used Y, whereas it should be X. Correct it.’ Stage 3, auditing before submission, requires use of the search function to check the consistency of every core term and the preparation of a frequency overview to determine whether X occurs as often as expected.

A practical example of such a lexicon would be to establish for Chapter 3 that ‘parental investment’ is the official term, that *kin bias*, *family care* and *parental devotion* must not be used, and that the reason is that Trivers (1972) uses this term and deviation would sever the

connection with the literature. The control instruction to the model would then be: ‘Scan Chapters 7–10 for synonyms for “parental investment”. Report every occurrence of: kin bias, family care, parental devotion, parental care. Replace them with “parental investment”.’

5.5 LESSON 4: Scope Discipline Prevents Digressions

The fourth fundamental finding concerns the tendency of AI to introduce relevant but off-topic themes, resulting in scope creep. The distinction between relevance and being on topic proves crucial for maintaining argumentative focus.

The evidence comes from several interventions. Intervention 104 responds to an attempt to introduce the Global North–South discussion: ‘Nuances are lost because data from the South are used in the North? Seriously? Decontextualisation is always a problem when data are used for a purpose other than that for which they were originally collected! But you are bringing the North–South discussion into it (undertone: “they in the South are poor, and that is our fault in the North”). All of that may well be true, but right now it is off topic!’ Intervention 105 then corrects the focus: ‘Concentrate on abuses of power surrounding the (inevitable) decontextualisation of data. On the scarcity of data as a raw material for AI-driven knowledge production.’ Intervention 147 illustrates the same pattern: ‘Furthermore, sustainability or not, this was about the reliability of AI-driven knowledge production and the CO_2 footprint neither adds to nor detracts from that. So it does not belong in this argument.’

The scientific implication is that relevance is not the same as being on topic. AI combines concepts that are related in a general sense. Decontextualisation of data is indeed a genuine problem, and North–South inequality is likewise an important issue, but the connection with AI-driven knowledge production is too indirect. This produces three problematic effects. First, scope creep occurs because the dissertation becomes too broad. Second, the argument weakens because causal claims are stretched too far. Third, off-topic discussions arise that reviewers would justifiably reject.

The solution lies in applying what may be called the **One-Hop Rule**: a concept is on topic if it can be connected to the research question in a single logical step. This can be tested using the research question: ‘How does AI affect the reliability of knowledge production?’ A valid connection would be: AI leads to black-box characteristics, which directly affect reliability. An invalid connection would be: AI requires data processing, which relates to North–South inequality, which ultimately affects reliability — this involves two hops and is therefore too indirect. The correction would be: AI requires decontextualisation of data, which directly affects reliability.

Practical implementation requires that, for every new section, the model be explicitly asked to explain in one sentence how the concept directly answers the research question, without intermediate steps. If the answer takes the form ‘this affects X, which subsequently affects Y’, the subject is off topic.

5.6 LESSON 5: Hallucination Control Requires External Verification

The fifth fundamental finding concerns the nature of AI hallucinations. These occur not only in references but also in factual claims about the case itself, and often take the form of blended recollections rather than pure fabrication.

The evidence comes from several instances of hallucination. Interventions 274–275 document a specific case: 'the controversy surrounding wealth taxation. If you found this, you really have the wrong document. […] No, I deliberately "threw out" wealth taxation in earlier versions because that case was far too thin and had far too little explanatory power.' Intervention 323 likewise identifies a hallucination: 'You are hallucinating. The first question in this study has nothing to do with polyglotism. Look only at the attached document.'

The scientific implication is that hallucinations are often not pure fabrications but blended recollections. AI combines earlier versions of documents, general domain knowledge and patterns from training data. This is more epistemologically dangerous than pure fabrication for three reasons. First, it sounds plausible because an earlier version did indeed contain wealth taxation. Second, it is partly true because wealth taxation is genuinely relevant to the domain. Third, it is nevertheless wrong because it does not occur in this version and does not belong in this particular study.

The solution requires implementation of a **three-layer verification protocol**. Layer 1, direct verification of every claim, requires asking the model on which page or in which section of the uploaded document the claim appears. If it cannot specify this, the claim should be treated as a hallucination. Layer 2, a consistency check for each chapter, requires compiling a list of all factual claims concerning cases, research questions and methods and checking these against Chapters 1–3. Any discrepancy is a potential hallucination. Layer 3, version control before submission, requires that, where earlier versions exist, an explicit list be compiled of material removed from those versions. This 'removed-items list' is then explicitly supplied to the model, after which the final version is scanned for the unexpected reappearance of deleted elements.

A practical application can be illustrated by a situation in which Version 1 contained 'wealth taxation' as a case and Version 2 replaced it with 'executive remuneration'. The protocol then requires the creation of a removed-items list containing wealth taxation, explicitly informing the model that wealth taxation no longer occurs in the dissertation, scanning Version 2 with zero results expected and, if references to wealth taxation nevertheless appear, stopping the process, correcting the error and regenerating the passage concerned.

5.7 LESSON 6: Methodological Vigilance as a Continuous Practice

The sixth fundamental finding concerns the need for continuous critical evaluation. Academic robustness does not arise spontaneously, but through the systematic application of critical questions, a process referred to in the chat history as the **Socratic method**.

The evidence comes from several interventions exposing methodological shortcomings. Intervention 54 states: 'So this is more of a methodological rationalisation than a data-analysis plan. Is that correct? We are going to answer sub-questions without a data-analysis and data-

collection plan? And can validity and reliability be meaningfully safeguarded without a concrete view of those plans?' Intervention 124 points to superficiality: 'It still comes across as somewhat superficial. Academic rigour requires this to refer clearly back to Chapters 4, 5 and 6, and to do so comprehensively: which opportunities/challenges/risks were identified in general terms, and which of these do or do not apply to this archetype, with argumentation?' Intervention 314 asks for concrete application: 'Are we actually applying the matrix here — checking the content of the cells corresponding to this archetype against the content of this case — or are we merely discussing the headings of the relevant columns?'

The scientific implication is that AI can generate form without substantive depth. Typical patterns include sections with appropriate headings but superficial content, unsupported claims that merely state that something 'demonstrates that', and references to earlier material without genuine integration. This is not a technical error but a fundamental limitation of the technology: AI reproduces patterns of academic texts without understanding their epistemological function.

The solution requires systematic application of what is termed the Socratic method. Five questions must be asked for every section. First: what exactly are you claiming here? This forces an explicit claim. Second: what is this based on? This forces the presentation of evidence. Third: how does this relate to Chapter X? This forces internal consistency. Fourth: what would a critic say about this? This forces counterweight. Fifth: why is this relevant to the research question? This forces the discussion to remain on topic.

The practical application can be demonstrated using a superficial paragraph. Suppose the model generates: 'The matrix shows that AI affects knowledge production. This has consequences for reliability.' The Socratic intervention would then proceed as follows. When asked what exactly is being claimed, the response must specify: 'AI affects the cognitive and methodological dimension by…' When asked what this is based on, it must cite: 'In Case 1, Section X showed that…' When asked how this relates to Chapter 4, it must establish the connection: 'This confirms the expectation in Chapter 4 that…' When asked what a critic would say, it must qualify the claim: 'A possible counterargument is that…' When asked why this is relevant, it must make explicit: 'This answers sub-question 1 by showing that…' The result of this systematic intervention is the transformation of two superficial sentences into eight academically robust sentences.

5.8 LESSON 7: Efficiency Comes from Directiveness, Not Politeness

The seventh and final fundamental finding concerns the relationship between communication style and efficiency. Short, directive interventions prove more efficient than polite explanations, an observation that contrasts with norms governing human-to-human interaction.

The evidence comes from the many short interventions in the chat history. Intervention 13 simply consists of 'Yep', as does intervention 29, while intervention 30 states: 'Yes, but with a count.' Intervention 71 is somewhat longer but remains direct: 'I don't believe that for a second, and it doesn't matter anyway; just reuse those texts, don't regenerate them.'

The scientific implication is that verbosity correlates negatively with efficiency in human–AI interaction. This can be explained by three factors. First, AI systems do not have feelings, so polite elaboration serves no epistemological function. Second, momentum is lost because

lengthy explanations invite further discussion. Third, clarity decreases because shorter instructions leave less room for ambiguity. This contrasts fundamentally with human-to-human interaction, in which politeness does serve a social function.

The solution requires implementation of what may be termed **command style** for routine decisions, with three levels of communication. Level 1, agreement, consists of a single word. When text is presented and the curator agrees, 'Yes', 'Yep' or 'Agreed' is sufficient, after which the process proceeds immediately to the next step. Level 2, conditional agreement, consists of one sentence. When text is presented and the curator agrees subject to a condition, 'Yes, but first count the number of words' is sufficient: this requires verification while accepting the overall direction. Level 3, rejection plus repair instruction, consists of no more than two sentences. When presented text is rejected, 'No, GPT disease. Reuse the original text from the previous version' is sufficient, without explaining why and with an immediate repair instruction.

The contrast with ineffective communication can be illustrated as follows. An ineffective response would be: 'Hmm, I don't think this is entirely right. The problem is that you have regenerated the text here even though I indicated that the original version should be preserved. Could you do this again, but this time without throwing away the original text?' This is ineffective because it contains three sentences instead of one, adopts an apologetic tone through expressions such as 'Hmm' and 'not entirely', and provides no clear instruction, relying instead on vague wording such as 'do this again, but this time'. An effective response, by contrast, would be: 'Regeneration. Reuse original text.' This is effective because it consists of two words of diagnosis plus two words of instruction, leaves no room for interpretation and is immediately actionable.

5.9 Reflection on the Analysis

Claude's analysis ends here. Its value lies not in its precise terminology or in the categorical force with which some conclusions are expressed. In particular, the characterisation of AI as a *'junior researcher'* is considered too narrow by the curator: in these projects, language models functioned more as broadly deployable knowledge and text systems whose value depended strongly on the task, the process context and the way in which their output was evaluated.

The analysis is nevertheless relevant because it identifies several behaviours that are repeatedly visible in the chat history: regeneration of curated text, terminological shifts, scope expansion, reflexive agreement, hallucinations and the need for concrete task delimitation. It therefore does not constitute an independent theory of human–AI collaboration, but a systematic reading of one exceptionally extensive production history. The concrete interventions on which the analysis is based are reproduced in Appendix 2.

The most concise summary of the curatorial lesson is less far-reaching than Claude's individual prescriptions: **structural discipline and process discipline**. Structural discipline concerns adherence to the research architecture, terminology and argumentative line; process discipline concerns delimiting tasks, preventing unnecessary regeneration and digressions, and checking model output before building further upon it. These two principles directly connect the analysis in this chapter to the risk-mitigation measures described in Chapter 4.

Chapter 6 – Source Verification

6.1 AI as a Proxy in Source Verification

Source verification constitutes a structural weak point in conventional academic practice. Supervisors and reviewers primarily assess the internal consistency of an argument, the plausibility of interpretations and its positioning in relation to existing literature. With extensive reference lists and interdisciplinary research, however, it is rarely practicable to examine systematically how every individual source has actually been used. The accuracy and proportionality of the use of sources therefore remain, to a significant extent, based on trust.

In this study, AI was therefore used not only for text production, but also as a **proxy in assessing the use of sources**. Its function is limited but relevant: language models can signal, at scale, where a source carries substantial argumentative weight, where its use deviates from common interpretations, or where there may be overloading, loss of context or substitution of argument by reference. This creates an additional systematic layer of control that is difficult to implement on a comparable scale in conventional research processes.

This function should explicitly not be understood as an independent test of truth. Without direct examination of the original source, a language model cannot establish what an author 'really' meant. It can, however, signal unusual or potentially problematic patterns on the basis of how authors, theories and concepts are represented in the available textual material. The model therefore functions as a detection instrument, not as an evaluative authority.

An explicit protocol was developed for this verification. The central questions are not whether a source exists, but what argumentative function it fulfils within the argument, how much of the argument depends upon it, whether it is used within the limits of its original reasoning, and whether its use displays signs of conceptual overloading, interpretative distortion, misuse of authority, selective reading, loss of context or substitution of argument by reference.

The quality of this form of verification depends strongly on the prompt used. Open questions such as 'Are the sources used correctly?' proved insufficiently precise. The final prompt was therefore designed as a procedural protocol in natural language, in which the purpose, assessment criteria, sequence of analysis and validation rules were explicitly specified. The model must first reconstruct the argument, then classify all sources according to argumentative dependency, assess only sources with medium or high dependency in substantive terms, and finally diagnose the use of sources as a whole. Summary, addition of new literature and free reinterpretation are explicitly excluded. The final prompt is included in Appendix 3.

The development of the prompt was itself iterative. Earlier versions proved too broad, too tolerant or too strongly focused on general plausibility. Testing and refinement produced a more controllable instrument. The human curator remained responsible both for designing the protocol and for interpreting its results. AI-based verification therefore does not replace academic control, but increases the capacity to identify potential problems systematically.

6.2 Results of the Verification of the Use of Sources

The final verification prompt was applied to the first eleven chapters of the dissertation. The empirical core of the dissertation begins in Chapter 12; the first eleven chapters primarily contain the conceptual, theoretical and methodological framework. The complete AI-generated analyses are reproduced without filtering in Appendix 4. The classification of the sources used produced the following picture:

Chapter	Number of sources used	Sources with medium/high argumentative dependency	%
1	15	8	53%
2	10	6	60%
3	17	11	65%
4	14	10	71%
5	11	10	91%
6	11	11	100%
7	7	6	86%
8	10	8	80%
9	8	8	100%
10	7	7	100%
11	7	7	100%

The system diagnoses by chapter were as follows:

Chapter	System Diagnosis
1	Strong framework centred on a small number of key sources; clear asymmetry towards critical AI literature; limited counterweight.
2	Strong dependency on literature concerning bias and reproducibility; cumulative reinforcement of a single thesis; risk of overgeneralisation.
3	Balanced but clustered around disciplinarity and interdisciplinarity; robust but with few opposing perspectives.
4	Empirically rich, with a clear tension between efficiency and quality; risk of cherry picking and case-based generalisation.
5	Focus on institutional mechanisms such as peer review and education; normatively coloured and with limited counterweight.
6	Strong normative governance framework centred on regulation, power and standards; clear asymmetry; risk of substitution by policy sources.
7	Clear contrast between success and failure of AI across domains; robust but relatively binary and susceptible to cherry picking.

Chapter	System Diagnosis
8	Reasonably balanced between innovation and criticism in digital humanities; slight clustering around loss of context.
9	Strong tension between classical ethnography and AI; normative preference for traditional methods; some conceptual redundancy.
10	Conceptually rich through the tension between Simon and Schön/Rittel; robust but potentially internally inconsistent without explicit positioning.
11	Coherent tension between automation and accountability; slight preference for critical literature; risk of substitution through surveys and position papers.

The proportion of sources with medium or high argumentative dependency clearly increases in the later theoretical chapters. This result requires cautious interpretation. It shows that sources fulfil different functions across chapters and that the later chapters rely more heavily on sources that are genuinely load-bearing for the argument. The analysis does not, however, make it possible to determine whether this difference results from AI-driven production, from the substantive function of the chapters, or from both.

A high proportion of load-bearing sources is not automatically an indicator of quality. It may reflect strong integration of literature into the argument, but it may also indicate concentration and therefore greater vulnerability if a limited number of key sources prove problematic. For this reason, the system diagnoses are more informative than the percentages in isolation. They reveal where the use of sources is relatively balanced and where the argument depends heavily on a restricted group of sources or perspectives.

The principal value of this verification is therefore not a generic conclusion that the use of sources is ‘good’, but a more differentiated picture of **where** the argument depends heavily on specific literature, **where** perspectives are underrepresented and **where** further human judgement remains necessary.

6.3 Results of the Bibliometric Verification

The bibliographic references in the dissertation were generated by language models. It could not be assumed that the model had direct access to the original sources or had copied every bibliographic detail from a controlled database. The accuracy of the references could therefore not be presumed in advance. They could range from entirely correct to partially incorrect or wholly fictitious.

A separate bibliometric verification was therefore conducted, focusing on two questions: do the cited sources actually exist, and are they bibliographically described correctly?

Category	Result
Fully correct references that exactly match international records	91%
Correct references after removal of AI artefacts, such as duplicate years or incorrect pagination	5%
Existing but incomplete references requiring supplementation	2%
Inconsistent, fragmented or untraceable references	2%

The complete bibliometric analysis is included in Appendix 5.

The result is strikingly positive: 96% of the references examined proved either correct or repairable through limited correction. Precisely because of this high score, additional methodological reflection was necessary.

6.4 Reflection — The Verification Paradox and the ALL

Verification of one hundred sources from the eleven theoretical chapters produced a result that seemed almost too favourable: approximately 96% of the references proved correct or readily repairable. Verification of the use of sources likewise revealed few obvious irregularities, while at the same time producing plausible analyses of the argumentative balance within each chapter. The first reaction was satisfaction. The second was suspicion. An exceptionally favourable result is itself a reason to scrutinise the measurement procedure.

This raised a more fundamental question: **what happens when one AI system evaluates text produced by another AI system?** Both systems operate through statistical pattern recognition in language. One system produces academically plausible text; the other assesses whether the use of sources and the argument correspond to patterns it recognises as plausible. This creates a genuine risk of circular confirmation. A second language model may constitute a separate control instrument, but that does not automatically make it an independent evaluator.

The verification model's initial response to this criticism was itself illustrative: it immediately endorsed the proposition that this amounted to a 'mirror test' and therefore to a fundamental methodological weakness. That response itself, however, required further scrutiny. The presence of circular elements in a verification method does not automatically render it worthless. The relevant question is which signals it can provide, which conclusions may legitimately be drawn from them, and where additional human control remains necessary.

A first limitation lies in the sample. Verification concentrated on the central sources within each chapter. These are precisely the sources most visible in the argument and are also likely to have been handled most carefully. Peripheral citations, one-off references and the long tail of the reference list were examined less intensively. The high scores therefore primarily concern the load-bearing core of the use of sources and should not automatically be generalised to every individual reference.

At the same time, circular validation is not equivalent to complete meaninglessness of the control procedure. Language models are trained on very large and heterogeneous text corpora containing different disciplines, authors, argumentative styles and forms of source use. In this

sense, they operate with a broad repertoire of patterns — referred to here as the **'ALL'**. It is plausible that this enables a model to signal unusual or inconsistent uses of sources. It does not, however, mean that the model possesses complete knowledge of the relevant literature or can independently establish whether a particular interpretation of a source is correct.

The verification did identify several points requiring attention. For example, in the case of Hao et al. (2024), it was noted that a preprint was used to support a broad claim even though the title of the article suggested a trade-off that was insufficiently reflected in the dissertation. In the case of Strubell et al. (2019), it was noted that an empirical article on energy costs was used within a broader argument concerning opacity. Such signals do not in themselves demonstrate incorrect source use, but they do identify specific locations where human checking is warranted.

This is precisely where human intervention remains necessary. The question of why the verification scores were so high did not arise from the original verification procedure itself, but from critical reflection on the result. The human contribution thereby shifts to another level: not every detail of verification needs to be performed manually, but the researcher must continue to question the validity of the control process itself, interpret anomalous outcomes and determine when additional verification is required.

The value of AI-driven verification therefore lies not in replacing human assessment, but in **scaling up detection**. A language model can rapidly signal patterns, potential inconsistencies and suspicious passages that can subsequently be investigated in a targeted manner. The benefit is that human attention can be concentrated on locations where the likelihood of problems is greatest.

The verification therefore demonstrates two things simultaneously. On the one hand, the load-bearing literature in the dissertation proved to have been used predominantly correctly and proportionately, and most bibliographic references were either correct or readily repairable. On the other hand, these findings are meaningful only within the limits of the verification methods used. They do not constitute an absolute claim to truth.

The central lesson is therefore not that AI can reliably certify its own output. It is that AI can provide a useful additional layer of control when the method is transparent, its limitations are made explicit, and the human curator remains responsible for interpreting both the results and the method itself.

Chapter 7 – Conclusions

The analysis of this process makes clear that AI-driven knowledge production cannot be reduced to text generation. The text of the dissertation was produced entirely by generative AI, while the research architecture, substantive and methodological direction, selection and evaluation of output, verification and ultimate responsibility remained with the human curator. The production process therefore rested on a clear distinction between textual authorship on the one hand and intellectual, methodological and curatorial responsibility on the other. The final product is neither the autonomous result of model capability nor a conventionally human-written dissertation, but the outcome of an iterative process in which human and artificial contributions continuously interacted.

Weaknesses and Preconditions of AI. The production histories show that language models can generate large quantities of coherent and academically plausible prose, while at the same time exhibiting recurrent limitations. These concern not only factual inaccuracies or hallucinations, but also overproduction, local coherence without sufficient safeguarding of global coherence, regeneration of already curated text, paraphrasing, terminological and semantic drift, incomplete processing of extensive documents and substantive instability in interaction with the curator. In addition, a structural asymmetry arises between the speed at which text can be produced and the time required to verify it carefully.

These findings provide no basis for assuming reliable autonomous knowledge production by language models within the production processes examined. At the same time, they show that such models can function highly productively when their use is embedded within an explicit process architecture. Structural discipline, process discipline, version control, precise task delimitation, functional separation between production and evaluation, and systematic verification proved particularly important. Nor does having large quantities of text available within a context window guarantee reliable preservation of the global architecture, the central argumentative thread or previously established conceptual distinctions. Safeguarding these remained a curatorial task throughout this process.

Academic Authorship. The process also shows that textual authorship and academic responsibility need not coincide. The curator did not formulate independent dissertation text or rewrite sentences generated by the models, but did design the research questions and methodological structure, introduce ideas, criticism and counterarguments, determine which output was accepted or rejected, and organise the successive stages of production and verification. The language models generated the final formulations and, through their proposals, interpretations and responses, simultaneously influenced the subsequent course of the production process.

Within this form of knowledge production, therefore, it is not so much authorship itself that shifts as the distribution of academic craftsmanship. Writing remains an essential function, but in this case was largely performed by language models. Human expertise manifested itself primarily in research design, questioning, substantive assessment, conceptual safeguarding, methodological criticism and decision-making. The language models did not function merely as passive instruments, but as active, though not independently responsible, actors within a process designed and supervised by the curator. Ultimate responsibility remained asymmetrically with the human.

Verification. A comparable division of labour became visible in the verification of the final product. The use of separate language models made it possible to examine the use of sources, argumentative dependencies and bibliographic references at a scale that would have made exclusively human verification highly labour-intensive. This use, however, also introduces the risk of circular confirmation: a language model evaluating the output of another language model operates from partly comparable linguistic and pattern structures.

The verification conducted therefore does not demonstrate that AI can independently certify its own output. It does show that language models can be useful as an additional detection layer. They can signal anomalies, inconsistencies and potentially problematic passages, thereby directing human attention towards areas where further examination is warranted. The interpretation of those signals, the assessment of the method and the decision whether additional verification was necessary remained with the curator. Within this framework, AI-based verification expands detection capacity but does not replace human judgement.

Transparency. A distinctive feature of this production process is the extent of the available process documentation. The three versions of the meta-dissertation are supported by more than 416,000 words and 1,300 pages of chat history. A complete forensic one-to-one mapping between every passage in the dissertation and every individual interaction could not be reconstructed efficiently, but the successive production, evaluation and revision stages are nevertheless documented to an exceptional degree.

This process-level visibility makes it possible to assess not only the final product as text, but also the manner in which it was produced. For a dissertation whose text was generated entirely by AI, this is not incidental but a necessary form of accountability. The claim of AI authorship is therefore not vested solely in the final product, but is supported by an extensive audit trail of interactions, versions, interventions and verification procedures.

Final Reflections. This Methodological Reflection Report does not demonstrate that AI-driven knowledge production is inherently reliable or automatically compatible with academic norms. Nor does it demonstrate that such knowledge production is fundamentally incompatible with those norms. What it does show is that a research process in which all final dissertation text is produced by generative AI can be organised in such a way that textual provenance, human direction, verification, limitations and ultimate responsibility remain explicit and auditable.

The legitimacy of such a process therefore rests not on any presumed reliability of the language model, but on the quality of the production process as a whole. Generative models can produce text, propose arguments, offer criticism, establish connections and perform control functions. They do not, however, independently bear responsibility for the research design, the validity of the choices made or the ultimate acceptance of the result. In this study, that responsibility remained with the curator.

At the same time, the result would be mischaracterised if AI were described merely as a passive instrument. What was achieved in this process could not have been realised without generative AI at this scale, speed and level of iterative intensity. The reverse is equally true: without human research architecture, substantive assessment, constraint, correction and verification, the model output would not have developed into a coherent and methodologically defensible dissertation.

The thousands of documented interactions therefore do not represent ‘push-of-a-button’ production, but a process in which human and machine continuously built upon each other’s

contributions. Their roles were different and their responsibilities asymmetrical, but both were necessary for the result achieved. In this functional sense, **the symbiosis between human and machine** may be the most accurate characterisation of this production process. The relevant question is therefore not whether the human is more intelligent than the machine, or vice versa, but what becomes possible when their different capabilities are combined within a carefully designed and critically supervised research process. The result achieved here could not have been produced by either independently.

APPENDIX 1:

Limited Reconstruction of Dissertation Versions

1. Characteristics of the Different Dissertation Versions

Version of the dissertation *AI-Driven Knowledge Production*	**Number of words**	**Number of pages**	**Case coverage**	**Production time**
Version 1	44,501	124	*1.Polyglot Learning in the AI Era*; 2. *Governing within Biological Boundaries*; 3. *AI-Driven Knowledge Production* (meta-case)	2 days
Version 2	52,281	141	*1.Polyglot Learning in the AI Era*; 2. *Governing within Biological Boundaries*; 3. *AI-Driven Knowledge Production* (meta-case)	4 days
Version 3	51,682	139	*1. Polyglot Learning in the AI Era*; 2. *Governing within Biological Boundaries*; 3. *Columba Loquens*; 4. *The Promises of Digital Revolutions*; 5. *AI-Driven Knowledge Production* (meta-case)	5 days

2. Relationship Between Chat Histories and Dissertation Versions

Version	**Chat history**	**Author**
Version 1	*Chat History: Production of Version 1 of the Dissertation AI-Driven Knowledge Development* (‘*Chatgeschiedenis Totstandkoming versie1 proefschrift AI-gestuurde kennisontwikkeling’*)	ChatGPT
Version 2	*Chat History: Production of Version 2 of the Dissertation AI-Driven Knowledge Development* (‘*Chatgeschiedenis Totstandkoming versie2 proefschrift AI-gestuurde kennisontwikkeling’*)	Claude
	Chat History: Completion of Version 2 of the Dissertation (Epilogue, Management Summary) (‘*Chatgeschiedenis Afronding totstandkoming versie 2 proefschrift (epiloog, management samenvatting)’*)	ChatGPT
Version 3	*Chat History: Production of Version 3 of the Dissertation AI-Driven Knowledge Development (Parts 1 and 2)* (‘*Chatgeschiedenis Totstandkoming versie3 proefschrift AI-gestuurde kennisontwikkeling (deel 1 en deel 2)*)’	ChatGPT

It should be noted that the Word document *Chat History: Production of Version 2 of the Dissertation AI-Driven Knowledge Development* (*Chatgeschiedenis Totstandkoming versie2 proefschrift AI-gestuurde kennisontwikkeling*) brings together ten technically separate chat histories relating to a single continuous revision process. They were merged into one Word document solely for ease of consultation. They al refer to one production process, and can logically not be considered as separate production trajectories. The division across multiple chats resulted from the practical limits on chat-history length encountered when working with Claude. In practice, these limits required the revision process to be continued in successive conversations (version 2); no comparable practical constraint was encountered when working with ChatGPT (versions 1 and 3).

The combined document contains the following ten chat histories: 1. *Chat 'Herschrijven hoofdstuk 8-9-10-11-12 proefschrift AI-gestuurde kennisontwikkeling'*, 2. *Chat 'Herschrijven hoofdstuk 13-14-15 proefschrift AI-gestuurde kennisontwikkeling'*, 3. *Chat 'Herschrijven hoofdstuk 7-16 proefschrift AI-gestuurde kennisontwikkeling'*, 4. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 1)'*, 5. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 2)'*, 6. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 3)'*, 7. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 4)'*, 8. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 5)'*, 9. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 6)'*, and 10. *Chat 'Tweede herziening tbv versie 2 proefschrift AI-gestuurde kennisproductie (deel 7).*

3. Size of the Chat Histories

Dissertation version	Chat-history record	Number of words	Number of pages
Version 1	*Chat History: Production of Version 1 of the Dissertation AI-Driven Knowledge Development* (*'Chatgeschiedenis Totstandkoming versie1 proefschrift AI-gestuurde kennisontwikkeling'*)	187,223	457
Version 2	*Chat History: Production of Version 2 of the Dissertation AI-Driven Knowledge Development* — merged record of ten successive chat histories (*'Chatgeschiedenis Totstandkoming versie2 proefschrift AI-gestuurde kennisontwikkeling'*)	44,074	202
	Chat History: Completion of Version 2 of the Dissertation (Epilogue, Abstract and Management Summary) (*'Chatgeschiedenis Afronding totstandkoming versie 2 proefschrift (epiloog, abstract, management samenvatting)'*)	13,663	48
Version 2 – total		**57,737**	**250**

Dissertation version	Chat-history record	Number of words	Number of pages
Version 3	*Chat History: Production of Version 3 of the Dissertation AI-Driven Knowledge Development – Part 1* (‘*Chatgeschiedenis Totstandkoming versie3 proefschrift AI-gestuurde kennisontwikkeling (deel 1)’*)	36,453	202
	Chat History: Production of Version 3 of the Dissertation AI-Driven Knowledge Development – Part 2 (‘*Chatgeschiedenis Totstandkoming versie3 proefschrift AI-gestuurde kennisontwikkeling (deel 2)’*)	135,210	459
Version 3 – total		**171,663**	**661**
Overall total		**416,623**	**1,368**

Given their size, the chat histories themselves — 416,623 words and 1,368 pages in total — have not been included in this reflection report. They are, however, available from the author upon request. The ratio Between Dissertation Length and Chat-History Length is as follows:

Version of the dissertation *AI-Driven Knowledge Production*	Number of words in dissertation	Number of words in corresponding chat histories	Ratio
Version 1	44,501	187,223	23.7%
Version 2	52,281	44,074 + 13,663 = 57,737	90.6%
Version 3	51,682	36,453 + 135,210 = 171,663	30.1%

4. Limitations of the Forensic Reconstruction

An attempt was made to enable an exact forensic reconstruction, for example in the form: *Section X of the dissertation was generated on page Y of the chat history recorded in document Z*. Such a reconstruction is not technically impossible, but in practice proved to be exceptionally labour-intensive. The language models themselves could not be used reliably as reconstruction tools. There are two reasons for this:

1. The tendency of language models to paraphrase rather than quote literally, which makes specific passages more difficult to retrieve exactly.
2. The tendency of language models to identify similarities through ‘pattern matching’ and ‘frequency analysis’. Such similarities need not constitute a literal match; they indicate a high probability rather than certainty.

In addition, three characteristics of the actual production and editing process complicate an exact one-to-one reconstruction:

A. The dissertation was generated version by version, chapter by chapter and section by section, with each section typically undergoing three to five iterations before approval. As a result, multiple closely resembling versions of the same section often exist. In most cases, the final version appearing in the chat history is also the version that ultimately entered the dissertation.

B. Because language models are unable, or only partially able, to 'patch' existing text, some modifications were implemented through 'search and replace' instructions, with the curator mechanically and literally executing the language model's instructions. This not only appears to reverse the normal division of labour, but is also particularly difficult for a human curator because language models tend to paraphrase. This method was therefore used only sparingly. In some cases, the curator also asked the language model to replace incomprehensible sentences containing substantial 'semantic compression' with an alternative that he could understand (*'Provide an alternative to sentence X'*). The replacement of X by Y is then traceable, but the resulting final text need not therefore occur as a single integral block of text in the chat history.

C. Finally, the dissertation texts underwent a limited final editing process. Anthropomorphic language was corrected — for example, *'the dissertation argues that …'* was replaced by *'it is argued in the dissertation that …'* — Anglicisms were removed, and minor but persistent language errors were corrected, such as *robuuste* instead of the correct Dutch *robuste*. It should also be noted that language models make remarkably few spelling errors; a higher concentration of spelling errors may therefore itself indicate human intervention.

These factors complicate a literal reconstruction, but do not make it impossible. A complete reconstruction would, however, constitute an exceptionally extensive exercise, while its additional methodological value would be limited.

Interestingly, this also accords with a recognised principle in forensic evaluation, related to Occam's Razor and likelihood-based reasoning: when an alternative explanation — such as fabrication or direct human authorship — demonstrably requires more actions, steps and complexity than producing the observed result itself, the plausibility of that alternative explanation decreases. Although this assessment necessarily remains probabilistic, the disproportion is substantial in this case: the production of a dissertation comprising 51,682 words and 139 pages is documented by a production process comprising 416,623 words and 1,368 pages of chat history. This ratio supports the proposition that the writing process cannot primarily be characterised as direct human authorship, but rather as a form of curated output generation in which the language model effectively produced the text.

APPENDIX 2: Analysis of Curator Interventions in the Efficient Production of Version 1 of the Dissertation

This appendix contains English translations verbatim excerpts from the chat history illustrating **how** the curator directed the process efficiently, ignored people-pleasing suggestions and circumvented recurrent pitfalls.

1. DIRECT, CONCISE DIRECTION — NO UNNECESSARY ELABORATION

Intervention 4: "Go ahead and create that framework, and we'll see where we go from there."

Intervention 6: "Seems useful to me."

Intervention 12: "Go ahead."

Intervention 13: "Yep."

Intervention 29: "Yep."

Intervention 30: "Yes, but with a count."

Pattern: No lengthy explanations and no people-pleasing: simply agreement or an immediate instruction to proceed. This prevents endless discussion and maintains momentum.

2. IGNORING PEOPLE-PLEASING SUGGESTIONS

Intervention 24: "This is too much at this point. And remember the Turing Test: the texts you write must not exude AI. So no staccato prose, no lists, but flowing text or academic prose, and no megalomaniacal tables."

Intervention 64: "A complete Chapter 3 — without throwing away any curated content — can you manage that too, you great please-machine?"

Intervention 71: "I don't believe that for a second, and it doesn't matter anyway; just reuse those texts, don't regenerate them."

Intervention 136: "No, certainly not shorter, but more academic and with a clear bridging function: I want the richly elaborated taxonomies back. How could you forget that?"

Intervention 232: "I think you are trying to please me here, but in my view it makes no sense whatsoever; the passage about the AI paradox is inappropriate."

Pattern: Immediately cutting off attractive-sounding additions that contribute no substantive value. Insisting that curated content must **NOT** be discarded.

3. CIRCUMVENTING PITFALLS — ENFORCING CONCEPTUAL PRECISION

Intervention 40: "'Time dynamics – How does AI change the pace of research and scientific careers?' I don't recognise this at all; it seems to me a misplaced paraphrase."

Intervention 65: "There really has been undesirable data reduction in this section. This is not an adaptation of an existing text, but complete regeneration. It does not do justice to the diversity of AI applications."

Intervention 160: "Note that deepfake technology only affects the quality of AI-driven knowledge production if it is actually used as such within that context. That is not the case in the texts you have written. The argument therefore loses its validity."

Intervention 233: "No, because we have not finished our discussion: good learning materials cannot indeed be assessed by a language learner, because that learner is unconsciously incompetent. And that is not what the AI paradox is about. There is, however, a serious methodological problem here: namely, who verifies whether the lexicons and learning materials generated by AI are valid and reliable? That is the issue that needs to be addressed. Not the paradox."

Intervention 269: "Correction: the writer is still the curator; the second GPT model has consistently provided criticism or counter-expertise, but how this was dealt with was always determined by the writer ('human in the loop')."

Intervention 282: "There is only one correct name for this mechanism: 'parental investment', and you are not going to deviate from it. The ten mechanisms in Chapter 3 constitute the uniform lexicon for the entire dissertation. I know there are still some paraphrases in the final sections, and I experience that as an irritating manifestation of GPT disease: your annoying tendency to paraphrase creates conceptual ambiguity that I then have to smooth out again."

Pattern: Whenever ChatGPT paraphrases, distorts concepts or adds material that is incorrect, it is corrected **IMMEDIATELY**. This prevents conceptual drift.

4. NO DIGRESSIONS — FOCUS ON THE CENTRAL QUESTION

Intervention 21: "No, I don't think this can simply be dropped in just like that. It needs an introduction first: why were the impact dimensions chosen in this way; what **justifies** this?"

Intervention 50: "No, I'm still not satisfied with 3.3, neither with the style (staccato, no academic prose) nor with the approach. I think the impact dimensions should be addressed first (in three separate chapters), after which these impact dimensions should be applied to each scientific domain (another 4+1 chapters)."

Intervention 104: "And I still have this nagging feeling: 'Why is this problematic when it comes to the quality of AI-driven knowledge production?' Nuances are lost because data from the South are used in the North? Seriously? Decontextualisation is always a problem when data

are used for a purpose other than that for which they were originally collected! But you are bringing the North–South discussion into it (undertone: 'they in the South are poor, and that is our fault in the North'). All of that may well be true, but right now it is off topic!"

Intervention 105: "Concentrate on abuses of power surrounding the (inevitable) decontextualisation of data. On the scarcity of data as a raw material for AI-driven knowledge production."

Intervention 147: "I think — and I acknowledge that I am partly responsible for this myself — that you should not look ahead towards the other archetypes. So 7.1 to 7.3 will have to be rewritten after all. Furthermore: sustainability or not, this was about the reliability of AI-driven knowledge production, and the CO_2 footprint neither adds to nor detracts from that. So it does not belong in this argument."

Intervention 322: "Yes, as long as the focus remains on the impact; the discussion should not be about all the injustice in the world. That would be off topic."

Pattern: Every attempt by ChatGPT to digress into side issues — North–South relations, sustainability, general inequality — is immediately redirected. The focus remains on the impact on AI-driven knowledge production.

5. PREVENTING GPT DISEASE — PRESERVING CURATED TEXT

Intervention 70: "This was simply a perfectly good text. Count the number of words before you rewrite it: [quotes the complete curated text]."

Intervention 72: "Yes, and with the source references as well, please (you may add material, but you may not remove anything)."

Intervention 135: "This really isn't good; a case of GPT disease."

Intervention 253: "For me, GPT disease is mainly about throwing away carefully curated texts, paraphrasing quotations so that process audits become very difficult, and persistently making promises that cannot be kept."

Intervention 255: "It can be put more forcefully: if 80% of a carefully curated text disappears during regeneration, that is 'bloody annoying' for the author who is using AI for support."

Intervention 256: "Go ahead and integrate it, please, without symptoms of GPT disease 😉."

Pattern: Systematically enforcing the preservation of good text during regeneration. This is crucial to efficiency.

6. METHODOLOGICAL VIGILANCE — CONTINUING TO ASK CRITICAL QUESTIONS

Intervention 54: "So this is more of a methodological rationalisation than a data-analysis plan. Is that correct? We are going to answer sub-questions without a data-analysis and data-collection plan? And can validity and reliability be meaningfully safeguarded without a concrete view of those plans?"

Intervention 92: "The latter. Control question. It is all reasonably sharp now and also explains much of the resistance to AI use in science. But the question is also, to some extent: is it really problematic? Perhaps existing rituals simply disappear to make way for newer, academically more meaningful rituals?"

Intervention 124: "It still comes across as somewhat superficial. Academic rigour requires this to refer clearly back to Chapters 4, 5 and 6, and to do so comprehensively: which opportunities/challenges/risks were identified in general terms, and which of these do or do not apply to this archetype, with argumentation?"

Intervention 304: "Control question: is the matrix applicable here or not?"

Intervention 314: "Are we actually applying the matrix here — checking the content of the cells corresponding to this archetype against the content of this case — or are we merely discussing the headings of the relevant columns?"

Pattern: Continuously asking critical questions about methodological choices. This prevents superficiality.

7. CONCRETE INSTRUCTIONS — NO VAGUE REQUESTS

Intervention 17: "What section structure do you have in mind? And this is supposed to become the introductory chapter. Have you already thought of a provisional chapter structure as well?"

Intervention 31: "Okay, now think about the structure of Chapter 2. It needs to address the research questions. Build up to them properly."

Intervention 45: "We're on the same page. I think Chapter 3 should deal with methodology: how are the research questions to be answered (with a data-analysis plan and data-collection plan for each sub-question), how do we keep the answers to these questions valid and reliable, and how do we position this research (using Saunders et al.?). I also want additional points of attention for each sub-question (everything that was lost when the questions were condensed into three sub-questions needs to find a place there). And concepts and definitions."

Intervention 75: "Chapter 4 in academic prose, please, but first collect some additional literature and tell me why you want to include it."

Intervention 125: "First work out the taxonomy in the intermezzo."

Pattern: Concrete, detailed instructions. Little room for ambiguity or people-pleasing.

8. CORRECTING HALLUCINATIONS IMMEDIATELY

Intervention 274: "'The controversy surrounding wealth taxation.' If you found this, you really have the wrong document. Do not rely on your memory; rely on the document I have just uploaded (Version 2.1)."

Intervention 275: "No, I deliberately 'threw out' wealth taxation in earlier versions because that case was far too thin and had far too little explanatory power. It was replaced by the 'executive remuneration' case. So I do not want to discuss wealth taxation anymore."

Intervention 281: "'Kin bias.' GPT disease! That term cannot be used."

Intervention 323: "You are hallucinating. The first question in this study has nothing to do with polyglotism. Look only at the attached document."

Pattern: Hallucinations are corrected **IMMEDIATELY**, without unnecessary discussion. This forces ChatGPT to work more precisely.

SYNTHESIS: WHY THE DEVELOPMENT OF VERSION 1 WAS SO EFFICIENT

1. **Short, direct instructions** — no endless discussions
2. **Immediately ignoring people-pleasing suggestions** — focus on substance
3. **Circumventing pitfalls through conceptual precision** — no drift
4. **No digressions** — remain strictly on topic
5. **Preventing GPT disease** — preserve curated text
6. **Methodological vigilance** — continue asking critical questions
7. **Concrete instructions** — no vague requests
8. **Correcting hallucinations immediately** — no discussion

Core insight: ChatGPT was treated as a junior researcher requiring tight direction, not as a 'wise adviser'. Whenever ChatGPT attempted to please, digress, paraphrase or hallucinate, it was corrected **IMMEDIATELY**, without accepting apologies. This explains the efficiency with which Version 1 was produced.

APPENDIX 3: Prompt for the Verification of the Use of Sources

The prompt reproduced below was used to analyse and verify the use of sources in the dissertation. For the benefit of the English-language reader, an English translation is presented first. The original Dutch-language prompt is reproduced immediately afterwards.

The Dutch version is the methodologically relevant original. The dissertation was generated through Dutch-language interactions with Claude and ChatGPT, and the source-verification procedure was likewise designed and executed in Dutch. The English version below is therefore a translation for accessibility and was not the prompt used in the actual verification process.

1. English translation

Prompt – Integrated Analysis of Source Use (Epistemologically Robust and Verifiable)

Analyse the use of sources in the text below as an epistemological system.
Avoid redundancy: classification and evaluation must derive from one and the same inference.

Step 0 – Frame of Reference (mandatory; perform first)

Formulate in no more than 150 words:

< what is argued and claimed in this text/dissertation section? >

This serves as the analytical anchor for all subsequent assessment.

Step 1 – Identification + Immediate Classification

Identify all explicit and implicit sources (authors, theories, concepts, schools of thought).

For each source, determine the degree of **argumentative dependency** on the basis of the cumulative criteria below:

High dependency if ≥3 of the following criteria apply:

1. The central claim of the argument falls away or changes substantially without this source
2. The source structures the argument (rather than merely supporting it)
3. Several key passages depend functionally on this source
4. Alternatives are not discussed or are implicitly excluded

Medium dependency if 1–2 criteria apply

Low dependency if none of these criteria apply (illustrative, contextual or rhetorical use)

⚠️ This classification must follow directly from your analysis; do not conduct a separate evaluation round.

Step 2 – Targeted Evaluation (only for medium/high dependency)

For each source with medium or high dependency:

- Which claim (from Step 0) is supported by this source?
- What is the nature of its use: necessary pillar or rhetorical anchor?
- Is the source used within the limits of its original argument?
- Explicitly assess the following six risks:
    1. Conceptual overloading
    2. Interpretative distortion
    3. Misuse of authority
    4. Selective reading (cherry picking)

5. Loss of context
6. Substitution of argument by reference

Integrate this assessment into one coherent analysis per source (no bullet points).

Step 3 – System Diagnosis

Assess the use of sources as a whole:

- Concentration of epistemological weight
- Vulnerability if key sources are removed
- Redundancy versus apparent diversity

Mandatory Output Format

0. Frame of Reference

< description of what is argued / claimed >

---

1. Complete Classification List (all sources)

For each source (ALWAYS include the full reference):

[Full reference] – Argumentative dependency: (low / medium / high)

---

2. Analysis of Medium/High Dependency

For each source (ALWAYS include the full reference):

[Full reference] – Argumentative dependency: (medium / high)

< description of what is argued / claimed within the dissertation using this source >

< description of the extent to which the use of the source satisfies the six criteria, including justification >

---

3. System Diagnosis (max. 200 words)

< integrated evaluation of source use as a system >

Validation Rules (mandatory)

- Every source must appear exactly once in the classification list
- Every source classified as “medium” or “high” must have exactly one analysis block
- The number of analysis blocks must exactly match the number of medium/high classifications
- If these conditions are not met: return an error message rather than a partial analysis

Instructions

- Work analytically and concisely
- Avoid descriptive summary
- Avoid duplication between classification and evaluation
- Use full references (no abbreviated names)

II. Original Dutch-language prompt used in the verification process

Prompt – Geïntegreerde analyse van brongebruik (epistemisch robuust en controleerbaar)

Analyseer het gebruik van bronnen in onderstaande tekst als een epistemisch systeem. Vermijd redundantie: classificatie en evaluatie moeten voortkomen uit één en dezelfde inferentie.

Stap 0 – Referentiekader (verplicht, eerst uitvoeren)

Formuleer in max. 150 woorden:

< wat wordt er in deze tekst/proefschriftonderdeel betoogd en geclaimd? >

Dit fungeert als analytisch anker voor alle verdere beoordeling.

Stap 1 – Identificatie + onmiddellijke classificatie

Identificeer alle expliciete en impliciete bronnen (auteurs, theorieën, concepten, scholen).

Bepaal per bron de mate van **argumentatieve afhankelijkheid** op basis van onderstaande cumulatieve criteria:

Hoge afhankelijkheid als ≥3 van de volgende criteria gelden:

1. De centrale claim van het betoog valt zonder deze bron weg of verandert wezenlijk
2. De bron structureert het argument (niet slechts ondersteunt)
3. Meerdere kernpassages leunen functioneel op deze bron
4. Alternatieven worden niet besproken of impliciet uitgesloten

Middelmatige afhankelijkheid als 1–2 criteria gelden

Lage afhankelijkheid als geen van deze criteria gelden (illustratief, contextueel, retorisch gebruik)

⚠️ Deze classificatie moet direct voortkomen uit je analyse; voer geen aparte evaluatieronde uit.

Stap 2 – Gerichte evaluatie (alleen voor middel/hoge afhankelijkheid)

Voor elke bron met middel of hoge afhankelijkheid:

- Welke claim (uit stap 0) wordt door deze bron gedragen?
- Wat is de aard van de inzet: noodzakelijke pijler of retorisch anker?
- Wordt de bron gebruikt binnen de grenzen van haar oorspronkelijke argumentatie?
- Beoordeel expliciet de volgende zes risico's:

1. Conceptuele overbelasting
2. Interpretatieve vertekening
3. Autoriteitsmisbruik
4. Selectieve lezing (cherry picking)
5. Contextverlies
6. Substitutie van argument door verwijzing

Integreer deze beoordeling in één samenhangende analyse per bron (geen bullet points).

Stap 3 – Systeemdiagnose

Beoordeel het brongebruik als geheel:

- Concentratie van epistemisch gewicht
- Kwetsbaarheid bij wegvallen sleutelbronnen
- Redundantie vs. schijn-diversiteit

Verplicht outputformat
0. Referentiekader

< omschrijving van wat er wordt betoogd / geclaimd >

---

1. Volledige classificatielijst (alle bronnen)

Per bron (ALTIJD volledige referentie opnemen):

[Volledige referentie] – Argumentatieve afhankelijkheid: (laag / middel / hoog)

---

2. Analyse van middel/hoge afhankelijkheid

Per bron (ALTIJD volledige referentie opnemen):

[Volledige referentie] – Argumentatieve afhankelijkheid: (middel / hoog)

< omschrijving van wat er wordt betoogd / geclaimd binnen het proefschrift m.b.v. deze bron >

< omschrijving van de mate waarin het gebruik van de bron voldoet aan de 6 criteria, inclusief motivatie >

---

3. Systeemdiagnose (max. 200 woorden)

< integrale evaluatie van het brongebruik als systeem >

Validatieregels (verplicht)

- Elke bron moet exact één keer voorkomen in de classificatielijst
- Elke bron met classificatie “middel” of “hoog” moet exact één analyseblok hebben
- Het aantal analyseblokken moet exact overeenkomen met het aantal middel/hoge classificaties
- Als deze voorwaarden niet worden gehaald: geef een foutmelding i.p.v. een gedeeltelijke analyse

---

Instructies

- Werk analytisch en compact
- Vermijd descriptieve samenvatting
- Vermijd doublures tussen classificatie en evaluatie
- Gebruik volledige referenties (geen verkorte namen)

APPENDIX 4:

Chapter-by-Chapter Analysis of the Use of Sources

4.1 Analysis of the Use of sources in Chapter 1

Frame of Reference

Chapter 1 argues that the impact of AI on science cannot be understood as a single homogeneous phenomenon, because both science and AI are internally differentiated. The chapter therefore introduces four archetypes of knowledge production and a meta-domain of AI development itself. The central claim is that AI changes the epistemological core of science, but that the nature of this change depends on both the type of science and the type of AI. At the same time, the chapter argues that classical scientific values such as interpretation, contextuality, reproducibility and normative accountability do not disappear, but come under pressure and require recalibration.

1. Complete Classification List (All Sources)

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922 – **Argumentative dependency: high**

Berry, D. M. (2012). *Understanding Digital Humanities.* Palgrave Macmillan. – **Argumentative dependency: low**

Boellstorff, T. (2021). *Virtual Society: Technology, Cyberculture, and Ethnography.* Princeton University Press. – **Argumentative dependency: low**

Burrell, J. (2016). *How the Machine "Thinks": Understanding Opacity in Machine Learning Algorithms. Big Data & Society, 3*(1), 1–12. https://doi.org/10.1177/2053951715622512 – **Argumentative dependency: medium**

Couldry, N., & Mejias, U. A. (2019). *The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism.* Stanford University Press. – **Argumentative dependency: medium**

Dean, J., Corrado, G., & Shazeer, N. (2021). *The Deep Learning Revolution and Its Implications for AI. Communications of the ACM, 64*(6), 58–65. https://doi.org/10.1145/3448250 – **Argumentative dependency: low**

Gadamer, H.-G. (2004). *Truth and Method* (2nd rev. ed., J. Weinsheimer & D. G. Marshall, Trans.). Continuum. (Original work published 1960). – **Argumentative dependency: medium**

Geertz, C. (1973). *The Interpretation of Cultures.* Basic Books. – **Argumentative dependency: medium**

Jumper, J., Evans, R., Pritzel, A., et al. (2021). *Highly Accurate Protein Structure Prediction with AlphaFold. Nature, 596*, 583–589. https://doi.org/10.1038/s41586-021-03819-2 – **Argumentative dependency: low**

Kania, E. (2019). *AI Weapons and China's Military Innovation. Texas National Security Review, 2*(1), 42–53. – **Argumentative dependency: low**

Popper, K. (1959). *The Logic of Scientific Discovery.* Hutchinson. – **Argumentative dependency: medium**

Real, E., Liang, C., So, D. R., & Le, Q. V. (2019). *AutoML-Zero: Evolving Machine Learning Algorithms From Scratch.* Proceedings of the 37th International Conference on Machine Learning, 8007–8019. – **Argumentative dependency: low**

Schön, D. A. (1983). *The Reflective Practitioner: How Professionals Think in Action.* Basic Books. – **Argumentative dependency: low**

Simon, H. A. (1969). *The Sciences of the Artificial.* MIT Press. – **Argumentative dependency: low**

Zhang, B., & Dafoe, A. (2019). *Artificial Intelligence: American Attitudes and Trends.* Oxford University Press. – **Argumentative dependency: low**

2. Analysis of Sources with Medium/High Argumentative Dependency

I. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922 – Argumentative dependency: high

< This source is used to argue that generic language models are neither neutral nor reliable, but structurally vulnerable to bias, fabrication and the appearance of understanding. Within Chapter 1, the source primarily supports the claim that generic AI cannot simply be trusted as an instrument of knowledge production and that the distinction between generic and domain-specific AI is fundamental. >

< The use of this source remains largely within the boundaries of its original argument, since Bender et al. do indeed warn of the epistemological and societal risks associated with large-scale language models. The source functions as a necessary pillar rather than merely as a rhetorical anchor. There is, however, a risk of conceptual overloading: criticism of large language models can too easily be extended to AI as a whole. Interpretative distortion is limited; the chapter mainly uses the source for the argument for which it is best known. Misuse of authority is not evident, although cherry picking becomes a risk if the benefits of generic models are not given comparable weight elsewhere. Loss of context is limited. The greatest risk lies in the substitution of argument by reference: the source may be made to do too much of the work in substantiating the claim that "AI does not really understand", without the dissertation itself developing that step further. >

II. Burrell, J. (2016). ***How the Machine "Thinks": Understanding Opacity in Machine Learning Algorithms. Big Data & Society,*** ***3***(1), 1–12. https://doi.org/10.1177/2053951715622512 – **Argumentative dependency: medium**

< This source is used to argue that AI systems are epistemologically problematic because their operation is often not transparent to users and researchers. In Chapter 1, it supports the claim that the black-box character of AI conflicts with classical scientific ideals of control and explainability. >

< The source functions as an analytical point of support and is used predominantly within the boundaries of its original argument. Burrell's distinctions concerning opacity are relevant to precisely this type of criticism. There is little evidence of misuse of authority. There is, however, some risk of interpretative narrowing: Burrell discusses opacity not only as a technical problem, but also as a social and institutional phenomenon. If the chapter reduces this primarily to a general claim that "AI is opaque", context is lost. Conceptual overloading is limited; the source is not required to carry the argument as a whole. Cherry picking is possible, but not strongly apparent. Substitution of argument by reference becomes a risk only if opacity is invoked without distinguishing between different types of AI systems. >

III. Couldry, N., & Mejias, U. A. (2019). ***The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism.*** **Stanford University Press. – Argumentative dependency: medium**

< This source is used to argue that AI is not merely a technical instrument, but is also embedded in broader power structures of data extraction and asymmetrical control. Within Chapter 1, the source primarily supports the claim that AI development is not neutral and that ownership, infrastructure and geopolitical relations help determine what can circulate as knowledge. >

< The source functions as a normative-critical anchor. Its use remains largely within the boundaries of the original argument as long as the chapter restricts itself to the proposition that data extraction and platform power have epistemological consequences. There is, however, a risk of conceptual overextension if every form of AI-supported knowledge production is immediately framed as "colonising". Interpretative distortion is possible if the specific analysis of data colonialism is reduced to a general critique of Big Tech. Misuse of authority is not evident. Selective reading becomes a risk when the source is used exclusively as a moral warning. Loss of context is a genuine risk, because Couldry and Mejias provide a broad societal framework that can easily be narrowed when incorporated into a philosophy-of-science argument. Substitution of argument by reference remains limited as long as the chapter independently explains how these power structures affect knowledge production. >

VI. Gadamer, H.-G. (2004). ***Truth and Method*** **(2nd rev. ed., J. Weinsheimer & D. G. Marshall, Trans.). Continuum. (Original work published 1960). – Argumentative dependency: medium**

< This source is used to argue that knowledge does not consist solely of accurate information processing, but also of interpretation within historical and contextual horizons. Within Chapter 1, Gadamer primarily supports the claim that, in disciplines such as history, meaning-making cannot be reduced to pattern recognition or statistical correlation. >

< The source functions here as a deep frame of reference, but not as a complete pillar of the chapter. Its use remains partly within the boundaries of the original argument as long as Gadamer is invoked to support the hermeneutic necessity of interpretation. There is, however, a clear risk of loss of context: Gadamer addresses human historicity, language and understanding, and this context disappears when his hermeneutics is applied directly as a standard for AI systems. Conceptual overloading is moderate; the source carries an important but not exclusive part of the argument. Interpretative distortion becomes a risk when the proposition that "AI does not understand" is derived too readily from Gadamer. Misuse of authority is limited. Cherry picking is possible if only the anti-positivist potential of his work is used. Substitution of argument by reference becomes a risk when Gadamer is treated as a self-evident refutation of computational models of knowledge without further elaboration. >

V. Geertz, C. (1973). ***The Interpretation of Cultures.*** **Basic Books. – Argumentative dependency: medium**

< This source is used to argue that, in anthropological research, meaning only becomes visible through thick description rather than through mere recording or data processing. Within Chapter 1, the source supports the claim that AI systems may detect patterns but struggle with contextually rich interpretation. >

< The source functions as an illustrative but important conceptual anchor. Its use remains largely within the boundaries of the original argument insofar as Geertz is used to emphasise the importance of context and interpretative density. There is a risk of conceptual simplification: thick description is a methodological orientation within anthropology, not a general formula for rejecting AI. Interpretative distortion is therefore possible if the concept is used too far outside its disciplinary context. Misuse of authority is not evident. Cherry picking is limited. Loss of context is nevertheless a genuine risk, because Geertz's work is strongly rooted in ethnographic practice. Substitution of argument by reference becomes a risk when "thick description" is used merely as a label for dismissing AI output as thin or superficial. >

VI. Popper, K. (1959). ***The Logic of Scientific Discovery.*** **Hutchinson. – Argumentative dependency: medium**

< This source is used to argue that natural-scientific knowledge rests on testability, reproducibility and falsification, and that AI output therefore cannot count as fully fledged scientific knowledge without independent testing. Within Chapter 1, Popper primarily supports the characterisation of natural-scientific research as an archetype organised around controllable causality and falsifiability. >

< The source functions as a methodological anchor for one archetype within the chapter. Its use remains broadly within the boundaries of the original argument as long as Popper is used to mark the logic of hypothesis and testing. There is, however, some risk of simplification because Popper functions here primarily as an emblem of natural-scientific method. Conceptual overloading is limited: the chapter as a whole does not depend on Popper, but uses him selectively for the first archetype. Interpretative distortion is moderately possible because more complex debates about scientific practice are reduced to falsification alone. Misuse of authority is not strongly evident. Cherry picking is plausible, although still defensible in an introductory chapter. Loss of context is present because Popper is used primarily as a concise methodological marker. Substitution of argument by reference remains limited as long as the chapter also independently explains why AI conflicts with reproducibility and causality. >

3. System Diagnosis

The use of sources in Chapter 1 is coherent but asymmetrically structured. Most of the argumentative weight rests on a small number of critical and epistemologically orienting sources: Bender et al. for the risks of generic language models, Popper for natural-scientific testability, and Gadamer/Geertz for the interpretative nature of knowledge in the humanities. This produces a clear framework, but also a degree of vulnerability: if one of these key sources were removed, a significant part of the chapter would lose its disciplinary anchor.

There is also a degree of apparent diversity at the periphery. Several low-dependency sources enrich the overview but contribute little to the core structure. Technically optimistic or empirically success-oriented sources, such as Dean et al. or Jumper et al., carry relatively little weight and therefore provide only limited counterbalance to the critical framework. The system is consequently analytically useful but normatively preconfigured: the chapter is stronger in identifying tensions than in balancing competing interpretations.

4.2 Analysis of the Use of sources in Chapter 2

Frame of Reference

Chapter 2 argues that the reliability and validity of scientific knowledge are under structural pressure from institutional and systemic factors such as publication pressure, bias and selection effects. It positions science not as a neutral truth-generating mechanism, but as a socially organised system in which incentives and power structures partly determine what is produced and validated as knowledge. At the same time, it argues that AI does not resolve these problems, but may amplify them by scaling up existing biases and epistemological vulnerabilities. The central claim is that both science and AI-driven knowledge production should be understood critically as fallible, context-dependent systems.

1. Complete Classification List (All Sources)

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the dangers of stochastic parrots: Can language models be too big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922 – **Argumentative dependency: medium**

Burrell, J. (2016). *How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society, 3*(1), 1–12. https://doi.org/10.1177/2053951715622512 – **Argumentative dependency: low**

Fanelli, D. (2010). *Do pressures to publish increase scientists' bias? An empirical support from US States Data. PLoS ONE, 5*(4), e10271. https://doi.org/10.1371/journal.pone.0010271 – **Argumentative dependency: high**

Gadamer, H.-G. (2004). *Wahrheit und Methode* (6th ed.). Tübingen: Mohr Siebeck. (Original work published 1960). – **Argumentative dependency: low**

Geertz, C. (1973). *The interpretation of cultures.* New York: Basic Books. – **Argumentative dependency: low**

Ioannidis, J. P. A. (2005). *Why most published research findings are false. PLoS Medicine, 2*(8), e124. https://doi.org/10.1371/journal.pmed.0020124 – **Argumentative dependency: high**

Kuhn, T. S. (2012). *The structure of scientific revolutions* (50th anniversary ed.). Chicago: University of Chicago Press. – **Argumentative dependency: medium**

Lawrence, P. A. (2003). *The politics of publication. Nature, 422*(6929), 259–261. https://doi.org/10.1038/422259a – **Argumentative dependency: medium**

Moosa, I. A. (2018). *Publish or perish: Perceived benefits versus unintended consequences.* Cheltenham: Edward Elgar. – **Argumentative dependency: medium**

Müller, V. C. (2020). *Ethics of artificial intelligence and robotics.* In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Fall 2020 Edition). https://plato.stanford.edu/archives/fall2020/entries/ethics-ai/ – **Argumentative dependency: low**

2. Analysis of Sources with Medium/High Argumentative Dependency

I. Fanelli, D. (2010). ***Do pressures to publish increase scientists' bias? An empirical support from US States Data. PLoS ONE, 5***(4), e10271. https://doi.org/10.1371/journal.pone.0010271 – **Argumentative dependency: high**

< This source is used to argue that publication pressure is systematically associated with increased bias in scientific outcomes. Within Chapter 2, this source supports the core claim that science can be distorted not only epistemologically, but also institutionally through incentive structures. >

< The source functions as an empirical pillar and is used largely within the boundaries of its original argument. Fanelli does indeed provide quantitative evidence of correlations between publication pressure and bias. There is little evidence of misuse of authority. There is, however, a risk of conceptual overloading when this correlation is treated as a general explanation for epistemological distortion in science. Interpretative distortion may occur if causal claims are made more strongly than the data justify. Cherry picking is possible if alternative explanations for bias remain outside the analysis. Loss of context is limited. Substitution of argument by reference becomes a risk when the complexity of scientific practice is reduced to a single empirical finding. >

II. Ioannidis, J. P. A. (2005). ***Why most published research findings are false. PLoS Medicine, 2***(8), e124. https://doi.org/10.1371/journal.pmed.0020124 – **Argumentative dependency: high**

< This source is used to argue that a substantial proportion of published scientific findings are systematically unreliable as a result of statistical, methodological and publication-related factors. Within Chapter 2, this source functions as a foundation for the claim that scientific knowledge production is structurally fallible. >

< The source functions as a central pillar and is used largely within the boundaries of its original argument. Ioannidis' model-based analysis directly supports the proposition of systematic unreliability. There is, however, a significant risk of interpretative overgeneralisation: the title and conclusion are often read more strongly than the underlying probabilistic reasoning warrants. Conceptual overloading becomes a risk when this single study is used as representative of science as a whole. Misuse of authority is not evident, but cherry picking is likely if countervailing literature is absent. Loss of context is a genuine risk because Ioannidis makes specific assumptions about research designs. Substitution of argument by reference is an important concern here: the source can too easily function as a conclusive authority without further differentiation. >

III. Kuhn, T. S. (2012). ***The structure of scientific revolutions*** **(50th anniversary ed.). Chicago: University of Chicago Press. – Argumentative dependency: medium**

< This source is used to argue that science does not accumulate linearly, but develops through paradigms and ruptures, implying that what counts as "true" is historically and socially conditioned. Within Chapter 2, Kuhn supports the claim that scientific knowledge is not independent of context and processes of consensus formation. >

< The source functions as a conceptual framework and is used broadly within the boundaries of the original argument. There is, however, a familiar risk of simplification: Kuhn is often reduced to relativism, whereas his analysis is more complex. Conceptual overloading is limited, but interpretative distortion becomes a risk when paradigms are linked too directly to bias or unreliability. Misuse of authority is not evident. Cherry picking is possible if only discontinuity is emphasised. Loss of context is present because Kuhn's historical analysis is translated into general epistemological claims. Substitution of argument by reference can occur when "paradigm" is used as an explanatory label without further elaboration. >

IV. Lawrence, P. A. (2003). ***The politics of publication. Nature, 422***(6929), 259–261. https://doi.org/10.1038/422259a **– Argumentative dependency: medium**

< This source is used to argue that publication processes are influenced by power, prestige and strategic behaviour, thereby affecting the selection of knowledge. Within Chapter 2, this source supports the claim that science is institutionally steered and does not operate as a purely meritocratic system. >

< The source functions as an empirical-illustrative anchor. Its use remains largely within the boundaries of the original argument, although there is a risk of overgeneralisation because the article is partly opinion-based in nature. Conceptual overloading is limited. Interpretative distortion is possible when specific observations are presented as structural regularities. Misuse of authority is not strongly evident. Cherry picking is plausible if alternative perspectives on publication practices are absent. Loss of context is limited. Substitution of argument by reference remains minor as long as the chapter combines several sources. >

V. Moosa, I. A. (2018). ***Publish or perish: Perceived benefits versus unintended consequences.*** **Cheltenham: Edward Elgar. – Argumentative dependency: medium**

< This source is used to argue that the 'publish or perish' culture has negative effects on the quality and integrity of scientific research. Within Chapter 2, this source supports the broader proposition that institutional incentives affect epistemological quality. >

< The source functions as a supplementary framework and is used largely within the boundaries of the original argument. Conceptual overloading is limited because the source addresses one particular aspect. Interpretative distortion is possible if the negative effects are presented as universal. Misuse of authority is not evident. Cherry picking is possible if only critical literature is used. Loss of context is limited. Substitution of argument by reference remains minor because the source is supplementary rather than foundational. >

VI. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). ***On the dangers of stochastic parrots: Can language models be too big?*** **Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922 – Argumentative dependency: medium**

< This source is used to argue that AI systems can amplify existing biases and epistemological problems rather than resolve them. Within Chapter 2, this source functions as a bridge between problems within science and comparable risks associated with AI. >

< The source functions as a critical connecting point and is used within the boundaries of its original argument. Conceptual overloading is limited because the source does not carry the central argument of the chapter. Interpretative distortion is possible when the specific criticism of language models is generalised to all AI. Misuse of authority is not evident. Cherry picking is possible if positive AI applications remain outside the analysis. Loss of context is limited. Substitution of argument by reference is minor. >

3. System Diagnosis

The use of sources in Chapter 2 is strongly concentrated around empirically grounded criticism of science itself, with Fanelli and Ioannidis functioning as the dominant pillars. This provides the argument with a solid foundation, but also creates dependency on a relatively small number of studies demonstrating systematic bias and unreliability. The combination with Kuhn and critiques of publication practices (Lawrence, Moosa) broadens the conceptual basis, but remains within the same critical register. This produces a cumulative effect: different sources reinforce the same proposition, increasing its persuasive force while also creating a risk of one-sidedness.

AI-related sources play a secondary role here and function primarily as a channel for extrapolation. Countervailing literature emphasising the reliability or self-correcting mechanisms of science is largely absent. The system is therefore internally consistent, but epistemologically asymmetrical and susceptible to overgeneralisation.

4.3 Analysis of the Use of Sources in Chapter 3

Frame of Reference

Chapter 3 argues that knowledge production is fundamentally structured by disciplinary and methodological arrangements, and that AI does not abolish these structures but reconfigures them. It introduces disciplines as epistemological cultures with their own norms, methods and validation criteria, and argues that interdisciplinarity is necessary but problematic because forms of knowledge are not straightforwardly compatible. At the same time, the chapter argues that AI as a technology can both transcend and reinforce these boundaries, depending on how it is used. The central claim is that AI-driven knowledge production can only be understood within the context of disciplinarily situated epistemologies and methodological regimes.

1. Complete Classification List (All Sources)

Becher, T., & Trowler, P. (2001). *Academic tribes and territories: Intellectual enquiry and the culture of disciplines* (2nd ed.). Open University Press. – **Argumentative dependency: high**

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the dangers of stochastic parrots: Can language models be too big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922 – **Argumentative dependency: medium**

Bhaskar, R. (2008). *A realist theory of science* (rev. ed.). Routledge. – **Argumentative dependency: medium**

Cooper, H. (2016). *Research synthesis and meta-analysis: A step-by-step approach* (5th ed.). Sage. – **Argumentative dependency: low**

Crawford, K. (2021). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence.* Yale University Press. – **Argumentative dependency: medium**

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage. – **Argumentative dependency: low**

Floridi, L. (2014). *The fourth revolution: How the infosphere is reshaping human reality.* Oxford University Press. – **Argumentative dependency: medium**

Frodeman, R. (2017). *Sustainable knowledge: A theory of interdisciplinarity.* Palgrave Macmillan. – **Argumentative dependency: medium**

Huutoniemi, K., Klein, J. T., Bruun, H., & Hukkinen, J. (2010). *Analyzing interdisciplinarity: Typology and indicators. Research Policy, 39*(1), 79–88. https://doi.org/10.1016/j.respol.2009.09.011 – **Argumentative dependency: medium**

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences.* Sage. – **Argumentative dependency: medium**

Knorr-Cetina, K. (1999). *Epistemic cultures: How the sciences make knowledge.* Harvard University Press. – **Argumentative dependency: high**

Maxwell, J. A. (2012). *A realist approach for qualitative research.* Sage. – **Argumentative dependency: low**

Pickstone, J. V. (2000). *Ways of knowing: A new history of science, technology, and medicine.* University of Chicago Press. – **Argumentative dependency: medium**

Repko, A. F., & Szostak, R. (2021). *Interdisciplinary research: Process and theory* (4th ed.). Sage. – **Argumentative dependency: medium**

Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson. – **Argumentative dependency: low**

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson. – **Argumentative dependency: low**

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education.* Polity Press. – **Argumentative dependency: low**

2. Analysis of the Use of Sources with Medium/High Argumentative Dependency

I. Becher, T., & Trowler, P. (2001). *Academic tribes and territories: Intellectual enquiry and the culture of disciplines* (2nd ed.). Open University Press. – Argumentative dependency: high

< This source is used to argue that disciplines function as social and epistemological communities with their own norms, methods and evaluation criteria. Within Chapter 3, this source provides the basis for the claim that knowledge production is not uniform, but strongly dependent on disciplinarily organised practices. >

< The source functions as a central pillar and is used largely within the boundaries of its original argument. Becher and Trowler do indeed analyse disciplines as 'tribes' with specific epistemological cultures. There is little evidence of misuse of authority. Conceptual overloading is limited, but may arise if the disciplinary model is used as a universal explanatory framework. Interpretative distortion is minor. Cherry picking is possible if variation within disciplines is ignored. Loss of context is limited. Substitution of argument by reference becomes a concern if the complexity of disciplinarity is not further developed within the dissertation itself. >

II. Knorr-Cetina, K. (1999). *Epistemic cultures: How the sciences make knowledge.* Harvard University Press. – Argumentative dependency: high

< This source is used to argue that different scientific domains employ fundamentally different modes of knowledge production, implying that there is no uniform epistemology of science. Within Chapter 3, this source supports the differentiation between knowledge regimes and legitimises the proposition that AI will interact differently with different epistemological cultures. >

< The source functions as an epistemological pillar and is used largely within the boundaries of its original argument. Knorr-Cetina's analysis of laboratory practices aligns well with the argument. There is limited risk of conceptual overloading, but there is a risk of simplification when complex empirical analyses are translated into general claims about disciplines. Interpretative distortion is possible through generalisation. Misuse of authority is not evident. Cherry picking may occur if only selected examples are used. Loss of context occurs when the specific empirical cases in the work disappear from view. Substitution of argument by reference is a genuine risk if the term "epistemic culture" is not developed further. >

III. Bhaskar, R. (2008). ***A realist theory of science*** **(rev. ed.). Routledge. – Argumentative dependency: medium**

< This source is used to argue that an underlying reality exists independently of our knowledge of it, but is accessible only indirectly through theories and methods. Within Chapter 3, this source supports the claim that different disciplines develop different modes of access to that reality. >

< The source functions as a philosophical framework. Its use remains largely within the boundaries of the original argument, although there is a risk of simplifying Bhaskar's complex critical realism. Conceptual overloading is limited. Interpretative distortion is possible when it is reduced to a general form of realism. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference may occur if the realist position is not developed further. >

IV. Bender, E. M., et al. (2021). ***On the dangers of stochastic parrots: Can language models be too big?*** **Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922 – Argumentative dependency: medium**

< This source is used to argue that AI systems lack understanding and therefore cannot operate independently within complex epistemological contexts such as disciplines. Within Chapter 3, this source supports the claim that AI cannot automatically function as an interdisciplinary producer of knowledge. >

< The source functions as a critical anchor. Its use remains within the boundaries of the original argument, although there is a risk of overgeneralising from language models to AI more broadly. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible if alternative perspectives are absent. Loss of context is limited. Substitution of argument by reference is minor. >

V. Crawford, K. (2021). ***Atlas of AI: Power, politics, and the planetary costs of artificial intelligence.*** **Yale University Press. – Argumentative dependency: medium**

< This source is used to argue that AI is embedded in material and political infrastructures, implying that disciplinarity and knowledge production are also shaped by power structures. >

< The source functions as a critical framework. Its use remains within the boundaries of the original argument, but may lead to normative amplification. Conceptual overloading is limited. Interpretative distortion is possible through generalisation. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs when concrete cases are abstracted away. Substitution of argument by reference is limited. >

VI. Floridi, L. (2014). ***The fourth revolution: How the infosphere is reshaping human reality.*** **Oxford University Press. – Argumentative dependency: medium**

< This source is used to argue that digital technologies, including AI, fundamentally alter the ways in which knowledge and reality are experienced. Within Chapter 3, this source supports the claim that disciplinarity is coming under pressure as a result of digitalisation. >

< The source functions as a philosophical anchor. Its use falls within the boundaries of the original argument, although there is a risk of abstraction and generalisation. Conceptual overloading is limited. Interpretative distortion is possible through simplification. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is possible. >

VI. Frodeman, R. (2017). ***Sustainable knowledge: A theory of interdisciplinarity.*** **Palgrave Macmillan. – Argumentative dependency: medium**

< This source is used to argue that interdisciplinarity is necessary for addressing complex problems, but epistemologically difficult to achieve. Within Chapter 3, this source supports the analysis of interdisciplinarity as problematic yet necessary. >

< The source functions as a conceptual framework. Its use remains largely within the boundaries of the original argument. Conceptual overloading is limited. Interpretative distortion is possible through a normative reading. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

VII. Huutoniemi, K., et al. (2010). ***Analyzing interdisciplinarity: Typology and indicators. Research Policy, 39***(1), 79–88. https://doi.org/10.1016/j.respol.2009.09.011 – **Argumentative dependency: medium**

< This source is used to argue that interdisciplinarity occurs in different forms and can be distinguished analytically. Within Chapter 3, this source supports differentiation within interdisciplinary research. >

< The source functions as an analytical instrument. Its use remains within the boundaries of the original argument, although it may be simplified. Conceptual overloading is limited. Interpretative distortion is minor. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

VIII. Kitchin, R. (2014). ***The data revolution: Big data, open data, data infrastructures and their consequences.*** **Sage. – Argumentative dependency: medium**

< This source is used to argue that data infrastructures transform knowledge production and enable forms of analysis that transcend disciplinary boundaries. >

< The source functions as a contextual framework. Its use remains within the boundaries of the original argument, although it may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is minor. >

IX. Pickstone, J. V. (2000). ***Ways of knowing: A new history of science, technology, and medicine.*** **University of Chicago Press. – Argumentative dependency: medium**

< This source is used to argue that different historical forms of knowledge production coexist, supporting the proposition that disciplines vary in their modes of knowing. >

< The source functions as a historical framework. Its use remains within the boundaries of the original argument, although it may be simplified. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

X. Repko, A. F., & Szostak, R. (2021). ***Interdisciplinary research: Process and theory*** **(4th ed.). Sage. – Argumentative dependency: medium**

< This source is used to argue that interdisciplinary research requires specific methodological steps and integration strategies. >

< The source functions as a methodological framework. Its use remains within the boundaries of the original argument, although it may be somewhat instrumental. Conceptual overloading is limited. Interpretative distortion is minor. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

3. System Diagnosis

The use of sources in Chapter 3 is relatively balanced, but has two clear centres of gravity: disciplinarity (Becher & Trowler; Knorr-Cetina) and interdisciplinarity (Frodeman; Huutoniemi; Repko). This combination creates a coherent analytical framework in which knowledge production is understood as differentiated and context-dependent.

The inclusion of philosophical sources (Bhaskar, Floridi) and critical AI sources (Bender, Crawford) broadens the perspective, but these remain secondary to the disciplinary-epistemological core argument. There is less extreme asymmetry than in the preceding chapters, although clustering around compatible perspectives remains evident.

The framework is reasonably robust: the argument does not depend on a single source, but on a cluster of sources. At the same time, countervailing perspectives remain limited; alternative views of disciplinarity or strongly integrative models of knowledge production are underrepresented.

4.4 Analysis of the Use of Sources in Chapter 4

Frame of Reference

Chapter 4 argues that AI-driven knowledge production is characterised in practice by a tension between efficiency and epistemological quality. On the one hand, AI tools increase the speed and scale of research, for example in systematic reviews; on the other hand, they introduce new risks such as hallucinations, oversimplification, amplification of bias and loss of depth. The chapter argues that these risks are not separate from existing problems in science, such as publication bias and reproducibility problems, but rather intensify them. The central claim is that AI increases scientific productivity while simultaneously placing the reliability and substantive richness of scientific knowledge under pressure.

1. Complete Classification List (All Sources)

Alkaissi, H., & McFarlane, S. I. (2023). *Artificial hallucinations in ChatGPT: Implications in scientific writing. Cureus, 15*(2), e35179. https://doi.org/10.7759/cureus.35179 – **Argumentative dependency: high**

Bernard, C. (2025). *Using AI for systematic review: the example of Elicit. BMC Medical Research Methodology, 25*(1), 1–10. https://doi.org/10.1186/s12874-025-02528-y – **Argumentative dependency: medium**

Borji, A. (2023). *A categorical archive of ChatGPT failures.* arXiv preprint, arXiv:2302.03494. – **Argumentative dependency: medium**

Erduran, S. (2024). *The impact of artificial intelligence on scientific practices. International Journal of Science Education, 46*(3), 325–343. https://doi.org/10.1080/09500693.2024.2306604 – **Argumentative dependency: medium**

Fabiano, C. (2024). *How to optimize the systematic review process using AI tools. JCPP Advances, 4*(1), e12234. https://doi.org/10.1002/jcv2.12234 – **Argumentative dependency: medium**

Fanelli, D. (2010). *"Positive" results increase down the hierarchy of the sciences. PLoS ONE, 5*(4), e10068. https://doi.org/10.1371/journal.pone.0010068 – **Argumentative dependency: low**

Gao, C. A., Howard, F. M., Markov, N. S., Dyer, E. C., Ramesh, S., Luo, Y., & Pearson, A. T. (2023). *Comparing scientific abstracts generated by ChatGPT to real abstracts with detectors and blinded human reviewers. npj Digital Medicine, 6*(1), 75. https://doi.org/10.1038/s41746-023-00819-6 – **Argumentative dependency: high**

Hao, D., Li, Y., & Wang, X. (2024). *AI expands scientists' impact but contracts science's focus.* arXiv preprint. https://arxiv.org/abs/2412.07727 – **Argumentative dependency: medium**

Ioannidis, J. P. A. (2005). *Why most published research findings are false. PLoS Medicine, 2*(8), e124. https://doi.org/10.1371/journal.pmed.0020124 – **Argumentative dependency: medium**

Kahneman, D., & Tversky, A. (1979). *Prospect theory: An analysis of decision under risk. Econometrica, 47*(2), 263–291. https://doi.org/10.2307/1914185 – **Argumentative dependency: low**

LiveScience. (2025, January 15). *AI chatbots oversimplify scientific studies and gloss over critical details — the newest models are especially guilty.* – **Argumentative dependency: low**

Messeri, L., & Crockett, Z. (2024, March 7). *Doing more, learning less: The risks of AI in research.* Yale News. – **Argumentative dependency: medium**

Nickerson, R. S. (1998). *Confirmation bias: A ubiquitous phenomenon in many guises. Review of General Psychology, 2*(2), 175–220. https://doi.org/10.1037/1089-2680.2.2.175 – **Argumentative dependency: low**

Open Science Collaboration. (2015). *Estimating the reproducibility of psychological science. Science, 349*(6251), aac4716. https://doi.org/10.1126/science.aac4716 – **Argumentative dependency: medium**

2. Analysis of Sources with Medium/High Argumentative Dependency

I. Alkaissi, H., & McFarlane, S. I. (2023). ***Artificial hallucinations in ChatGPT: Implications in scientific writing. Cureus, 15***(2), e35179. https://doi.org/10.7759/cureus.35179 – **Argumentative dependency: high**

< This source is used to argue that AI systems, particularly language models, systematically generate hallucinations that undermine the reliability of scientific texts. Within Chapter 4, this source provides direct empirical support for the claim that AI-generated knowledge cannot be trusted without verification. >

< The source functions as a central empirical pillar. Its use remains largely within the boundaries of the original argument, but there is a clear risk of conceptual overloading: specific observations concerning ChatGPT may be generalised to AI-driven knowledge production as a whole. Interpretative distortion is possible if the frequency and severity of hallucinations are not qualified. Misuse of authority is not evident. Cherry picking is plausible if only negative cases are emphasised. Loss of context is limited. Substitution of argument by reference is an important risk when this source is treated as conclusive evidence without additional empirical differentiation. >

II. Gao, C. A., et al. (2023). ***Comparing scientific abstracts generated by ChatGPT to real abstracts with detectors and blinded human reviewers. npj Digital Medicine, 6***(1), 75. https://doi.org/10.1038/s41746-023-00819-6 – **Argumentative dependency: high**

< This source is used to argue that AI-generated scientific texts are difficult to distinguish from genuine abstracts, with implications for quality control and validation in science. Within

Chapter 4, this source supports the claim that AI not only introduces errors, but also makes those errors more difficult to detect. >

< The source functions as a strong empirical pillar and is used largely within the boundaries of the original argument. There is, however, a risk of interpretative overgeneralisation: the study is context-specific, concerning abstracts in a particular setting, but may be interpreted more broadly. Conceptual overloading becomes a risk if the finding is presented as representative of all scientific communication. Misuse of authority is not evident. Cherry picking is possible if other studies with less pronounced findings are absent. Loss of context occurs when the experimental conditions are abstracted away. Substitution of argument by reference is a genuine risk if the study is used as decisive evidence. >

III. Bernard, C. (2025). ***Using AI for systematic review: the example of Elicit. BMC Medical Research Methodology,*** ***25***(1), 1–10. https://doi.org/10.1186/s12874-025-02528-y – **Argumentative dependency: medium**

< This source is used to argue that AI tools can substantially increase the efficiency of systematic reviews. Within Chapter 4, this source supports the positive side of AI use in science. >

< The source functions as an empirical counterweight. Its use remains within the original argument, but may be instrumental. Conceptual overloading is limited. Interpretative distortion is possible if efficiency is equated with quality. Misuse of authority is not evident. Cherry picking is possible if negative findings are omitted. Loss of context is limited. Substitution of argument by reference is minor. >

IV. Borji, A. (2023). ***A categorical archive of ChatGPT failures.*** **arXiv preprint, arXiv:2302.03494. – Argumentative dependency: medium**

< This source is used to argue that AI systems systematically make errors that can be organised into categories. Within Chapter 4, this source supports the proposition that AI failure is structural and amenable to analysis. >

< The source functions as an illustrative empirical anchor. Its use remains within the original argument, but there is a risk of cherry picking because the source explicitly constitutes a collection of failures. Conceptual overloading is limited. Interpretative distortion is likely if this collection is regarded as representative. Misuse of authority is not evident. Loss of context is present because the selection criteria are not always clear. Substitution of argument by reference is limited. >

V. Erduran, S. (2024). ***The impact of artificial intelligence on scientific practices. International Journal of Science Education,*** ***46***(3), 325–343. https://doi.org/10.1080/09500693.2024.2306604 – **Argumentative dependency: medium**

< This source is used to argue that AI changes scientific practices at the level of methods, evaluation and education. Within Chapter 4, this source supports the broader contextualisation of AI's impact. >

< The source functions as a conceptual framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible.

Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

VI. Fabiano, C. (2024). ***How to optimize the systematic review process using AI tools. JCPP Advances,*** ***4***(1), e12234. https://doi.org/10.1002/jcv2.12234 – **Argumentative dependency: medium**

< This source is used to argue that AI can bring concrete methodological improvements to research processes. Within Chapter 4, this source supports the pragmatic use of AI in science. >

< The source functions as a methodological anchor. Its use remains within the original argument, but may be instrumental. Conceptual overloading is limited. Interpretative distortion is possible if effectiveness is overstated. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

VII. Hao, D., Li, Y., & Wang, X. (2024). ***AI expands scientists' impact but contracts science's focus.*** **arXiv preprint. https://arxiv.org/abs/2412.07727 – Argumentative dependency: medium**

< This source is used to argue that AI increases the impact of science while at the same time potentially narrowing the diversity of research questions. Within Chapter 4, this source supports the paradox of efficiency versus epistemological narrowing. >

< The source functions as an analytical anchor. Its use remains within the original argument, but there is a risk of overgeneralising preliminary findings because of its preprint status. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VIII. Ioannidis, J. P. A. (2005). ***Why most published research findings are false. PLoS Medicine,*** ***2***(8), e124. https://doi.org/10.1371/journal.pmed.0020124 – **Argumentative dependency: medium**

< This source is used to argue that scientific knowledge was already structurally vulnerable before AI. Within Chapter 4, this source supports the proposition that AI amplifies existing problems. >

< The source functions as a contextual foundation. Its use remains within the original argument, but there is a risk of overgeneralisation. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is possible. >

IX. Messeri, L., & Crockett, Z. (2024). ***Doing more, learning less: The risks of AI in research.*** **Yale News. – Argumentative dependency: medium**

< This source is used to argue that the use of AI can lead to more superficial understanding despite higher productivity. Within Chapter 4, this source supports the central paradox of efficiency versus depth of knowledge. >

< The source functions as an illustrative-normative anchor. Its use falls partly within the original argument, but there is a clear risk of misuse of authority because this is a journalistic source. Conceptual overloading is limited. Interpretative distortion is possible. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is a point of concern. >

X. Open Science Collaboration. (2015). ***Estimating the reproducibility of psychological science. Science,*** ***349***(6251), aac4716. https://doi.org/10.1126/science.aac4716 – **Argumentative dependency: medium**

< This source is used to argue that reproducibility in science is problematic independently of AI. Within Chapter 4, this source supports the claim that AI may amplify existing vulnerabilities. >

< The source functions as an empirical foundation. Its use remains within the original argument, but there is a risk of overgeneralisation beyond psychology. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through extrapolation. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 4 is strongly empirically oriented and relatively well balanced between critical and instrumental perspectives on AI. The core of the argument rests on two types of sources: (1) studies demonstrating the limitations and risks of AI (Alkaissi, Gao, Borji), and (2) studies demonstrating benefits in terms of efficiency and application (Bernard, Fabiano). The chapter's central tension — efficiency versus epistemological quality — is therefore consistently supported. At the same time, there is a clear asymmetry: critical sources carry greater argumentative weight and are developed more extensively than the positive applications.

There is also an elevated risk of cherry picking and overgeneralisation because several sources are based on case studies, preprints or selected examples of failure. The system is reasonably robust, but its robustness depends on the extent to which these empirical fragments are representative of broader AI practices.

4.5 Analysis of the Use of Sources in Chapter 5

Frame of Reference

Chapter 5 argues that the societal impact of science is determined not only by substantive quality, but also by institutional mechanisms such as peer review, evaluation criteria and educational practices. It argues that these mechanisms are historically developed and normatively charged, and that AI does not transform these systems neutrally but restructures them. In particular, the chapter argues that AI affects both the evaluation of research, for example through peer review and impact measurement, and the transmission of knowledge through education. The central claim is that AI fundamentally changes the institutions that regulate scientific quality and impact, thereby creating new risks and normative questions concerning validation, integrity and education.

1. Complete Classification List (All Sources)

Bastow, S., Dunleavy, P., & Tinkler, J. (2014). *The impact of the social sciences: How academics and their research make a difference.* SAGE. https://doi.org/10.4135/9781473957947 – **Argumentative dependency: medium**

Becher, T., & Trowler, P. R. (2001). *Academic tribes and territories: Intellectual enquiry and the culture of disciplines* (2nd ed.). Open University Press. – **Argumentative dependency: medium**

Biagioli, M. (2002). *From book censorship to academic peer review. Emergences: Journal for the Study of Media & Composite Cultures, 12*(1), 11–45. https://doi.org/10.1080/1045722022000003430 – **Argumentative dependency: high**

Crawford, K. (2021). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence.* Yale University Press. – **Argumentative dependency: medium**

Holmes, W., Bialik, M., & Fadel, C. (2021). *Artificial intelligence in education: Promises and implications for teaching and learning.* UNESCO. – **Argumentative dependency: medium**

Knox, J. (2020). *Artificial intelligence and education futures: Critical perspectives on learning, knowledge and culture.* Routledge. – **Argumentative dependency: medium**

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education.* Pearson. – **Argumentative dependency: low**

Moher, D., Bouter, L., Kleinert, S., Glasziou, P., Sham, M. H., Barbour, V., … & Dirnagl, U. (2020). *The Hong Kong principles for assessing researchers: Fostering research integrity. PLoS Biology, 18*(7), e3000737. https://doi.org/10.1371/journal.pbio.3000737 – **Argumentative dependency: medium**

Müller-Birn, C., Dobusch, L., & Seitz, S. (2020). *Peer review in the age of artificial intelligence. Science and Public Policy, 47*(6), 749–759. https://doi.org/10.1093/scipol/scaa039 – **Argumentative dependency: high**

Prinsloo, P., & Slade, S. (2017). *An elephant in the learning analytics room: The case for critical research in learning analytics.* In *Learning Analytics: Fundaments, Applications, and Trends*, 105–128. Springer. https://doi.org/10.1007/978-3-319-52977-6_6 – **Argumentative dependency: medium**

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education.* Polity Press. – **Argumentative dependency: medium**

2. Analysis of the Use of Sources with Medium/High Argumentative Dependency

I. Biagioli, M. (2002). ***From book censorship to academic peer review. Emergences: Journal for the Study of Media & Composite Cultures, 12***(1), 11–45. https://doi.org/10.1080/1045722022000003430 – **Argumentative dependency: high**

< This source is used to argue that peer review has historically functioned not merely as a quality mechanism, but also as a system of control and selection related to earlier forms of knowledge regulation such as censorship. Within Chapter 5, this source supports the claim that evaluative mechanisms in science are normatively and institutionally shaped. >

< The source functions as a central pillar and is used largely within the boundaries of the original argument. Biagioli's historical analysis legitimises the proposition that peer review is not a neutral filter. There is, however, a risk of interpretative overextension if the analogy with censorship is pushed too far. Conceptual overloading is possible if this single historical trajectory is used as a general explanation for all evaluative practices. Misuse of authority is not evident. Cherry picking is plausible if alternative interpretations of peer review are absent. Loss of context occurs when the historical detail is abstracted away. Substitution of argument by reference is a genuine risk if the complexity of contemporary peer review is not further developed. >

II. Müller-Birn, C., Dobusch, L., & Seitz, S. (2020). ***Peer review in the age of artificial intelligence. Science and Public Policy, 47***(6), 749–759. https://doi.org/10.1093/scipol/scaa039 – **Argumentative dependency: high**

< This source is used to argue that AI transforms the peer-review process through automation, scaling and new forms of evaluation. Within Chapter 5, this source supports the claim that AI intervenes directly in the core mechanisms of scientific validation. >

< The source functions as a central empirical-conceptual pillar. Its use remains largely within the original argument, but there is a risk of overgeneralising from specific developments to the peer-review system as a whole. Conceptual overloading is possible if the source is treated as representative of all AI interventions. Interpretative distortion may occur through normative framing. Misuse of authority is not evident. Cherry picking is plausible if alternative developments are absent. Loss of context occurs through abstraction. Substitution of argument

by reference becomes a concern if the dissertation itself does not specify how AI changes these processes. >

III. Bastow, S., Dunleavy, P., & Tinkler, J. (2014). ***The impact of the social sciences: How academics and their research make a difference.*** **SAGE. https://doi.org/10.4135/9781473957947 – Argumentative dependency: medium**

< This source is used to argue that the impact of science should be understood more broadly than academic publications alone, and that societal relevance constitutes an important dimension. Within Chapter 5, this source supports a broadening of evaluation criteria. >

< The source functions as a normative framework. Its use remains within the original argument, although it may be generalising. Conceptual overloading is limited. Interpretative distortion is possible when used normatively. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

IV. Becher, T., & Trowler, P. R. (2001). ***Academic tribes and territories: Intellectual enquiry and the culture of disciplines*** **(2nd ed.). Open University Press. – Argumentative dependency: medium**

< This source is used to argue that disciplines apply different norms for quality and evaluation. Within Chapter 5, this source supports the claim that peer review and impact assessment vary across disciplines. >

< The source functions as a conceptual framework. Its use remains within the original argument, although it may be simplified. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

V. Crawford, K. (2021). ***Atlas of AI: Power, politics, and the planetary costs of artificial intelligence.*** **Yale University Press. – Argumentative dependency: medium**

< This source is used to argue that AI systems are embedded in structures of power, with implications for who produces and evaluates knowledge. Within Chapter 5, this source supports the critical analysis of AI in evaluative systems. >

< The source functions as a critical framework. Its use remains within the original argument, but may reinforce the normative orientation of the analysis. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VI. Holmes, W., Bialik, M., & Fadel, C. (2021). ***Artificial intelligence in education: Promises and implications for teaching and learning.*** **UNESCO. – Argumentative dependency: medium**

< This source is used to argue that AI can transform educational practices, including assessment and knowledge transfer. Within Chapter 5, this source supports the discussion of AI's role in educational contexts. >

< The source functions as a policy framework. Its use remains within the original argument, although it may be normative. Conceptual overloading is limited. Interpretative distortion is possible through an overly optimistic reading. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

VII. Knox, J. (2020). ***Artificial intelligence and education futures: Critical perspectives on learning, knowledge and culture.*** **Routledge. – Argumentative dependency: medium**

< This source is used to argue that AI in education is not neutral, but restructures knowledge, culture and learning. Within Chapter 5, this source supports the critical analysis of AI in education. >

< The source functions as a critical anchor. Its use remains within the original argument, but may be normatively charged. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is limited. Substitution of argument by reference is minor. >

VIII. Moher, D., et al. (2020). ***The Hong Kong principles for assessing researchers: Fostering research integrity. PLoS Biology, 18***(7), e3000737. https://doi.org/10.1371/journal.pbio.3000737 – **Argumentative dependency: medium**

< This source is used to argue that new evaluation principles are needed to safeguard research integrity. Within Chapter 5, this source supports normative proposals concerning evaluation. >

< The source functions as a normative framework. Its use remains within the original argument, although it may be policy-oriented. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

IX. Prinsloo, P., & Slade, S. (2017). ***An elephant in the learning analytics room: The case for critical research in learning analytics.*** **In** ***Learning Analytics: Fundaments, Applications, and Trends***, 105–128. Springer. https://doi.org/10.1007/978-3-319-52977-6_6 – **Argumentative dependency: medium**

< This source is used to argue that data-driven educational practices require critical scrutiny because of their implications for privacy and power. Within Chapter 5, this source supports the critical approach to AI in education. >

< The source functions as a critical framework. Its use remains within the original argument, although it may be normative. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is limited. Substitution of argument by reference is minor. >

X. Selwyn, N. (2019). ***Should robots replace teachers? AI and the future of education.*** **Polity Press. – Argumentative dependency: medium**

< This source is used to argue that AI redefines the role of teachers and educational practices. Within Chapter 5, this source supports the broader discussion of AI in knowledge transfer. >

< The source functions as a critical-reflective anchor. Its use remains within the original argument, although it may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

3. System Diagnosis

The use of sources in Chapter 5 is concentrated around two core mechanisms: (1) the evaluation of knowledge through peer review and impact assessment, and (2) the transmission of knowledge through education. The combination of Biagioli and Müller-Birn provides a strong core for the analysis of the transformation of peer review, while the educational literature covers the second domain.

The system is reasonably balanced, but has a clear normative orientation: many sources emphasise risks, power structures and critical perspectives. Positive or more neutral perspectives on AI-driven evaluation and education are less prominent.

The robustness of the source base is moderate: the argument does not depend on a single source, but it does rest on a limited number of core ideas, particularly criticism of peer review and AI in education. There is a risk of conceptual clustering, whereby different sources reinforce similar normative claims without strong internal counterargument.

4.6 Analysis of the Use of Sources in Chapter 6

Frame of Reference

Chapter 6 argues that AI-driven knowledge production is not only an epistemological and methodological issue, but also a governance issue. It argues that the development and application of AI are highly concentrated among a limited number of actors, creating power asymmetries that affect knowledge production, access and control. At the same time, the chapter argues that this concentration and the associated risks have given rise to a growing field of regulation, standards and ethical frameworks, such as model cards, datasheets and international guidelines. The central claim is that reliable AI-driven knowledge production depends on institutional safeguards, transparency and regulation, but that these frameworks are themselves normatively and politically charged.

1. Complete Classification List (All Sources)

Biagioli, M. (2002). *From book censorship to academic peer review. Emergences, 12*(1), 11–45. – **Argumentative dependency: medium**

Brookings Institution / GovAI. (2023). *Analyses of foundation model concentration and market power* [Policy reports]. – **Argumentative dependency: high**

Couldry, N., & Mejías, U. A. (2019). *The costs of connection: How data is colonizing human life and appropriating it for capitalism.* Stanford University Press. – **Argumentative dependency: medium**

European Union. (2024). *Artificial Intelligence Act.* Official Journal of the European Union. – **Argumentative dependency: high**

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé III, H., & Crawford, K. (2018). *Datasheets for datasets. Communications of the ACM, 64*(12), 86–92. – **Argumentative dependency: high**

Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., ... & Gebru, T. (2019). *Model cards for model reporting.* Proceedings of the Conference on Fairness, Accountability, and Transparency, 220–229. – **Argumentative dependency: high**

NIST. (2023). *Artificial Intelligence Risk Management Framework (AI RMF 1.0).* National Institute of Standards and Technology. – **Argumentative dependency: medium**

OECD. (2019). *OECD Principles on Artificial Intelligence.* Organisation for Economic Co-operation and Development. – **Argumentative dependency: medium**

Strubell, E., Ganesh, A., & McCallum, A. (2019). *Energy and policy considerations for deep learning in NLP.* Proceedings of the 57th Annual Meeting of the ACL, 3645–3650. – **Argumentative dependency: medium**

UNESCO. (2021). *Recommendation on the Ethics of Artificial Intelligence.* United Nations Educational, Scientific and Cultural Organization. – **Argumentative dependency: medium**

Zuboff, S. (2019). *The age of surveillance capitalism.* PublicAffairs. – **Argumentative dependency: high**

2. Analysis of the Use of Sources with Medium/High Argumentative Dependency

I. Brookings Institution / GovAI. (2023). *Analyses of foundation model concentration and market power* [Policy reports]. – Argumentative dependency: high

< This source is used to argue that the development of AI, particularly foundation models, is highly concentrated among a small number of organisations, resulting in market power and control over knowledge infrastructures. Within Chapter 6, this source supports the core claim that AI-driven knowledge production is institutionally and economically concentrated. >

< The source functions as a central empirical-institutional pillar. Its use remains largely within the boundaries of the original argument, but there is a risk of conceptual overloading if specific market analyses are generalised to all forms of AI. Interpretative distortion is possible when preliminary policy analyses are presented as structural regularities. Misuse of authority is limited, although the policy context requires caution. Cherry picking is plausible if other market analyses are absent. Loss of context occurs when specific cases are abstracted away. Substitution of argument by reference is an important risk if the concentration thesis is not developed further. >

II. European Union. (2024). *Artificial Intelligence Act.* Official Journal of the European Union. – Argumentative dependency: high

< This source is used to argue that AI regulation is necessary to manage risks and safeguard trust in AI systems. Within Chapter 6, this source supports the claim that governance frameworks play a central role in AI-driven knowledge production. >

< The source functions as a normative and legal pillar. Its use remains within the original purpose of the legislation, but there is a risk of interpretative simplification of complex regulation. Conceptual overloading is possible if a single regulatory framework is presented as representative of global governance. Misuse of authority is not evident, although the normative force of the legislation may be adopted implicitly without critical reflection. Cherry picking is possible if only European regulation is discussed. Loss of context occurs through abstraction. Substitution of argument by reference is a genuine risk when legislation serves as self-evident legitimation. >

III. Gebru, T., et al. (2018). *Datasheets for datasets. Communications of the ACM, 64*(12), 86–92. – Argumentative dependency: high

< This source is used to argue that transparency concerning datasets is essential to responsible AI development. Within Chapter 6, this source supports the claim that standardisation and documentation are crucial to reliable knowledge production. >

< The source functions as a technical-normative pillar. Its use remains within the original argument, but there is a risk of overgeneralising from one type of documentation practice. Conceptual overloading is possible if datasheets are presented as a solution to broader governance problems. Interpretative distortion is limited. Misuse of authority is not evident. Cherry picking is possible if alternative approaches are absent. Loss of context occurs through abstraction. Substitution of argument by reference is a point of concern. >

IV. Mitchell, M., et al. (2019). ***Model cards for model reporting.*** **Proceedings of the Conference on Fairness, Accountability, and Transparency, 220–229. – Argumentative dependency: high**

< This source is used to argue that transparency concerning AI models is necessary for evaluation and accountability. Within Chapter 6, this source supports the claim that AI systems must be documented in order to remain epistemologically auditable. >

< The source functions as a technical pillar and is used largely within the boundaries of the original argument. Conceptual overloading is possible if model cards are regarded as a sufficient solution. Interpretative distortion is limited. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is a genuine risk if implementation problems are not discussed. >

V. Zuboff, S. (2019). ***The age of surveillance capitalism.*** **PublicAffairs. – Argumentative dependency: high**

< This source is used to argue that digital technologies, including AI, are embedded in economic systems oriented towards data collection and behavioural steering. Within Chapter 6, this source supports the claim that AI-driven knowledge production cannot be separated from capitalist power structures. >

< The source functions as a critical-theoretical pillar. Its use remains within the original argument, but there is a substantial risk of conceptual overloading if all AI developments are placed within this framework. Interpretative distortion is possible through a normative reading. Misuse of authority is not evident, although the rhetorical force of the work may carry considerable weight. Cherry picking is plausible if alternative economic interpretations are absent. Loss of context occurs through abstraction. Substitution of argument by reference is an important concern. >

VI. Biagioli, M. (2002). ***From book censorship to academic peer review. Emergences, 12***(1), 11–45. – **Argumentative dependency: medium**

< This source is used to argue that systems of knowledge regulation are historically rooted and contain normative dimensions. Within Chapter 6, this source supports the analogy between classical and modern forms of knowledge control. >

< The source functions as a historical anchor. Its use remains within the original argument, but there is a risk of overextending historical analogies. Conceptual overloading is limited.

Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VII. Couldry, N., & Mejías, U. A. (2019). *The costs of connection: How data is colonizing human life and appropriating it for capitalism.* Stanford University Press. – Argumentative dependency: medium

< This source is used to argue that data extraction and AI are connected to broader forms of social and economic domination. Within Chapter 6, this source supports the critical analysis of AI governance. >

< The source functions as a normative framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VIII. NIST. (2023). *Artificial Intelligence Risk Management Framework (AI RMF 1.0).* National Institute of Standards and Technology. – Argumentative dependency: medium

< This source is used to argue that AI risks can be analysed and managed systematically through standardised frameworks. Within Chapter 6, this source supports the operationalisation of AI governance. >

< The source functions as a practical framework. Its use remains within the original argument, although it may be instrumental. Conceptual overloading is limited. Interpretative distortion is possible through a normative reading. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

IX. OECD. (2019). *OECD Principles on Artificial Intelligence.* Organisation for Economic Co-operation and Development. – Argumentative dependency: medium

< This source is used to argue that international principles provide direction for responsible AI development. Within Chapter 6, this source supports the globalisation of AI governance. >

< The source functions as a normative framework. Its use remains within the original argument, but may be abstract. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

X. Strubell, E., Ganesh, A., & McCallum, A. (2019). *Energy and policy considerations for deep learning in NLP.* Proceedings of the 57th Annual Meeting of the ACL, 3645–3650. – Argumentative dependency: medium

< This source is used to argue that AI systems entail substantial ecological and energy costs. Within Chapter 6, this source supports the claim that AI governance also encompasses environmental dimensions. >

< The source functions as an empirical anchor. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible.

Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through extrapolation. Substitution of argument by reference is limited. >

XI. UNESCO. (2021). *Recommendation on the Ethics of Artificial Intelligence.* United Nations Educational, Scientific and Cultural Organization. – Argumentative dependency: medium

< This source is used to argue that ethical guidelines are necessary for responsible AI. Within Chapter 6, this source supports the normative basis of AI governance. >

< The source functions as a normative framework. Its use remains within the original argument, but may be abstract. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 6 is strongly concentrated around governance, regulation and power. The core of the argument rests on three pillars: (1) concentration in AI development (Brookings), (2) regulation and standardisation (EU AI Act, datasheets, model cards), and (3) critical analysis of power structures (Zuboff).

This combination creates a coherent and strongly normative framework, but also a clear epistemological asymmetry: virtually all sources support the need for regulation and problematise existing power structures. Counter-perspectives, such as market-driven innovation without extensive regulation, are almost entirely absent.

The source base is reasonably robust, but its robustness depends on the extent to which policy and normative documents are treated as empirical evidence. There is an elevated risk of substitution of argument by reference, particularly where standards and guidelines are presented as self-evidently legitimate.

4.7 Analysis of the Use of Sources in Chapter 7

Frame of Reference

Chapter 7 argues that the impact of AI on knowledge production is not uniform, but varies substantially across domains. In some scientific fields, such as biology and astronomy, AI leads to breakthroughs and accelerates discovery, whereas in other contexts, such as generative language models, limitations and errors become apparent. The chapter therefore introduces a differential approach to AI: the epistemological value of AI depends on the type of problem, the nature of the data and the extent to which expertise remains integrated. The central claim is that AI is not a generic knowledge instrument, but a technology whose epistemological performance must be assessed on a domain-by-domain basis.

1. Complete Classification List (All Sources)

Borji, A. (2023). *A categorical archive of ChatGPT failures.* arXiv preprint arXiv:2302.03494. – **Argumentative dependency: medium**

Brookings Institution / GovAI. (2023). *Analyses of foundation model concentration and market power.* – **Argumentative dependency: low**

Collins, H., & Evans, R. (2007). *Rethinking expertise.* University of Chicago Press. – **Argumentative dependency: high**

Fluke, C. J., & Jacobs, C. (2020). *Surveying the reach and maturity of machine learning and artificial intelligence in astronomy. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(2), e1349. – **Argumentative dependency: medium**

Jumper, J., et al. (2021). *Highly accurate protein structure prediction with AlphaFold. Nature, 596*(7873), 583–589. – **Argumentative dependency: high**

Rolnick, D., et al. (2019). *Tackling climate change with machine learning.* arXiv preprint arXiv:1906.05433. – **Argumentative dependency: medium**

Valenti, S., et al. (2021). *Machine learning applications for exoplanet detection. Astronomy & Astrophysics, 645*, A62. https://doi.org/10.1051/0004-6361/202039448 – **Argumentative dependency: medium**

2. Analysis of the Use of Sources with Medium/High Argumentative Dependency

I. Collins, H., & Evans, R. (2007). *Rethinking expertise.* University of Chicago Press. – Argumentative dependency: high

< This source is used to argue that expertise is essential to the interpretation and validation of knowledge, and that not all knowledge is equally accessible in the absence of domain-specific competencies. Within Chapter 7, this source supports the central claim that AI can function effectively only within domains in which human expertise remains adequately integrated. >

< The source functions as a conceptual pillar and is used largely within the boundaries of the original argument. Collins and Evans' distinction between different types of expertise aligns well with the differential approach to AI. There is limited risk of conceptual overloading, although simplification may occur when complex forms of expertise are reduced to a general argument against generic AI. Interpretative distortion is possible through normative application. Misuse of authority is not evident. Cherry picking is possible if alternative perspectives on expertise are absent. Loss of context occurs through abstraction from the detailed sociological analyses. Substitution of argument by reference is a concern if expertise is used as a self-evident criterion without further operationalisation. >

II. Jumper, J., et al. (2021). *Highly accurate protein structure prediction with AlphaFold. Nature, 596*(7873), 583–589. – Argumentative dependency: high

< This source is used to argue that AI can lead to significant scientific breakthroughs in specific domains, such as protein-structure prediction. Within Chapter 7, this source supports the positive pole of the argument: AI can be highly effective in well-structured domains. >

< The source functions as an empirical pillar and is used largely within the boundaries of the original argument. There is, however, a risk of conceptual overloading when this breakthrough is presented as representative of AI performance in general. Interpretative distortion is possible when extrapolating to other domains. Misuse of authority is not evident, although the status of the work may carry considerable weight. Cherry picking is plausible if less successful applications are absent. Loss of context occurs through abstraction from the specific biomedical context. Substitution of argument by reference is a genuine risk if this case is used as evidence of general AI capability. >

III. Borji, A. (2023). *A categorical archive of ChatGPT failures.* arXiv preprint arXiv:2302.03494. – Argumentative dependency: medium

< This source is used to argue that generative AI systems systematically make errors, limiting their applicability as general-purpose producers of knowledge. Within Chapter 7, this source supports the negative pole of the argument: AI fails in less structured or context-rich domains. >

< The source functions as an illustrative-empirical anchor. Its use remains within the original argument, but there is a clear risk of cherry picking because the source is explicitly focused on failures. Conceptual overloading is limited. Interpretative distortion is likely if this collection

is regarded as representative. Misuse of authority is not evident. Loss of context occurs because of the absence of systematic selection criteria. Substitution of argument by reference is limited. >

IV. Fluke, C. J., & Jacobs, C. (2020). ***Surveying the reach and maturity of machine learning and artificial intelligence in astronomy. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10***(2), e1349. – **Argumentative dependency: medium**

< This source is used to argue that AI has a growing but still immature role in astronomy, dependent on data quality and methodological integration. Within Chapter 7, this source supports the qualification that AI performance varies within domains. >

< The source functions as an empirical framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible through abstraction. Misuse of authority is not evident. Cherry picking is possible. Loss of context is present. Substitution of argument by reference is limited. >

V. Rolnick, D., et al. (2019). ***Tackling climate change with machine learning.*** **arXiv preprint arXiv:1906.05433. – Argumentative dependency: medium**

< This source is used to argue that AI can contribute to complex societal problems such as climate change, but that such applications depend on context and implementation. Within Chapter 7, this source supports the broader applicability of AI beyond strictly scientific domains. >

< The source functions as an illustrative framework. Its use remains within the original argument, but there is a risk of overgeneralising from potential to realised impact. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VI. Valenti, S., et al. (2021). ***Machine learning applications for exoplanet detection. Astronomy & Astrophysics, 645***, **A62. https://doi.org/10.1051/0004-6361/202039448 – Argumentative dependency: medium**

< This source is used to argue that AI can be deployed effectively for specific detection tasks in astronomy. Within Chapter 7, this source supports the proposition that AI performs well in clearly defined problem spaces. >

< The source functions as an empirical anchor. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible through extrapolation. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 7 is clearly structured around a central contrast: successful domain-specific AI applications versus failing generic AI systems. This contrast is empirically supported by cases from biology and astronomy on the positive side and generative AI on the negative side, with Collins and Evans providing the conceptual link through their analysis of expertise.

The system is relatively robust because it does not depend on a single source, but on a configuration of complementary examples. At the same time, there is a clear risk of cherry picking: both successes and failures are selected to support the central proposition.

The epistemological balance is reasonable, but remains binary in structure. Intermediate positions, such as partially successful applications with mixed outcomes, are less visible, which may lead to oversimplification of the variation in AI performance.

4.8 Analysis of the Use of Sources in Chapter 8

Frame of Reference

Chapter 8 argues that AI and digitisation techniques in the humanities enable new forms of knowledge production, while at the same time introducing epistemological shifts and risks. It argues that methods such as text mining, digitisation and automated transcription increase scale and accessibility, but can also lead to loss of context, interpretative depth and historical awareness. The central claim is that digital and AI-driven methods are not neutral, but reconfigure the nature of historical and literary knowledge, generating both new insights and systematic distortions.

1. Complete Classification List (All Sources)

Borji, A. (2023). *A categorical archive of ChatGPT failures.* arXiv preprint arXiv:2302.03494. – **Argumentative dependency: low**

Jockers, M. (2013). *Macroanalysis: Digital Methods and Literary History.* University of Illinois Press. – **Argumentative dependency: high**

Kahle, P., Colutto, S., Hackl, G., & Fiel, S. (2017). *Transkribus – A Service Platform for Transcription, Recognition and Retrieval of Historical Documents.* ICDAR 2017 Proceedings, 19–24. – **Argumentative dependency: medium**

Ketelaar, E. (2001). *Tacit Narratives: The Meanings of Archives. Archival Science, 1*, 131–141. – **Argumentative dependency: medium**

Putnam, L. (2016). *The Transnational and the Text-Searchable: Digitized Sources and the Shadows They Cast. American Historical Review, 121*(2), 377–402. – **Argumentative dependency: high**

Terras, M. (2011). *Digital Curiosities: Resource Creation Via Amateur Digitisation. Literary and Linguistic Computing, 26*(4), 425–438. – **Argumentative dependency: medium**

Underwood, T. (2019). *Distant Horizons: Digital Evidence and Literary Change.* University of Chicago Press. – **Argumentative dependency: high**

Verhoeven, D. (2016). *Doing Digital Humanities: An Extended Review. Digital Scholarship in the Humanities, 31*(1), 1–15. – **Argumentative dependency: low**

Wevers, M., & Smits, T. (2020). *The politics of the machine: Digital humanities and the automation of text analysis. Digital Scholarship in the Humanities, 35*(1), 194–214. – **Argumentative dependency: medium**

Zwierlein, C. (2016). *Anachronism and Antiquarianism: Historical Knowledge and its Uses.* Routledge. – **Argumentative dependency: medium**

2. Analysis of the Use of Sources with Medium/High Argumentative Dependency

I. Jockers, M. (2013). *Macroanalysis: Digital Methods and Literary History.* University of Illinois Press. – Argumentative dependency: high

< This source is used to argue that large-scale computational analysis of texts enables new insights into literary history that cannot be achieved through traditional close reading. Within Chapter 8, this source supports the claim that digitisation and AI fundamentally change the scale and nature of analysis in the humanities. >

< The source functions as a central pillar for the potential of digital methods. Its use remains largely within the boundaries of the original argument, but there is a risk of conceptual overloading if macroanalysis is presented as a generally applicable method. Interpretative distortion is possible if limitations, such as loss of context, receive insufficient attention. Misuse of authority is not evident. Cherry picking is plausible if successful applications are emphasised disproportionately. Loss of context is an inherent risk that may not be problematised sufficiently. Substitution of argument by reference is a point of concern if the methodological implications are not developed further. >

II. Putnam, L. (2016). *The Transnational and the Text-Searchable: Digitized Sources and the Shadows They Cast. American Historical Review, 121*(2), 377–402. – Argumentative dependency: high

< This source is used to argue that the digitisation of sources enables new research practices while simultaneously introducing selective visibility and distortion. Within Chapter 8, this source supports the critical claim that digital sources 'cast shadows' and thereby distort the historical picture. >

< The source functions as a critical pillar and is used within the boundaries of the original argument. There is limited risk of conceptual overloading, although there is some risk of generalising specific problems of digitisation to all digital methods. Interpretative distortion is minor. Misuse of authority is not evident. Cherry picking is possible if positive effects receive less attention. Loss of context is an inherent part of the analysis and is explicitly recognised here. Substitution of argument by reference is limited. >

III. Underwood, T. (2019). *Distant Horizons: Digital Evidence and Literary Change.* University of Chicago Press. – Argumentative dependency: high

< This source is used to argue that computational methods generate new forms of evidence concerning literary change over time. Within Chapter 8, this source supports the claim that digital analysis can be epistemologically productive. >

< The source functions as an important pillar in legitimising digital methods. Its use remains within the boundaries of the original argument, but there is a risk of conceptual overloading if this approach is presented as a general model. Interpretative distortion is possible if complex methods are simplified. Misuse of authority is not evident. Cherry picking is plausible if only successful applications are discussed. Loss of context is a recognised risk within distant reading

and may itself form part of the argument. Substitution of argument by reference is a point of concern. >

IV. Kahle, P., Colutto, S., Hackl, G., & Fiel, S. (2017). ***Transkribus – A Service Platform for Transcription, Recognition and Retrieval of Historical Documents.*** **ICDAR 2017 Proceedings, 19–24. – Argumentative dependency: medium**

< This source is used to argue that AI-driven transcription and recognition substantially increase the accessibility of historical sources. Within Chapter 8, this source supports the practical possibilities offered by digitisation. >

< The source functions as a technical-empirical anchor. Its use remains within the original argument, although it may be instrumental. Conceptual overloading is limited. Interpretative distortion is possible if effectiveness is overstated. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

V. Ketelaar, E. (2001). ***Tacit Narratives: The Meanings of Archives. Archival Science, 1*****, 131–141. – Argumentative dependency: medium**

< This source is used to argue that archives are not neutral, but carry meanings that depend on context and interpretation. Within Chapter 8, this source supports the claim that digitisation may impoverish these implicit layers of meaning. >

< The source functions as a conceptual anchor. Its use remains within the original argument, but there is a risk of simplifying complex archival practices. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

VI. Terras, M. (2011). ***Digital Curiosities: Resource Creation Via Amateur Digitisation. Literary and Linguistic Computing, 26***(4), 425–438. – **Argumentative dependency: medium**

< This source is used to argue that digitisation often takes place through heterogeneous and non-standardised processes, with consequences for data quality. Within Chapter 8, this source supports the claim that digital datasets are not inherently reliable. >

< The source functions as an empirical-critical anchor. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VII. Wevers, M., & Smits, T. (2020). ***The politics of the machine: Digital humanities and the automation of text analysis. Digital Scholarship in the Humanities, 35***(1), 194–214. – **Argumentative dependency: medium**

< This source is used to argue that the automation of text analysis is not neutral, but has political and epistemological implications. Within Chapter 8, this source supports the critical reflection on digital humanities. >

< The source functions as a critical framework. Its use remains within the original argument, but may be normatively charged. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VIII. Zwierlein, C. (2016). ***Anachronism and Antiquarianism: Historical Knowledge and its Uses.*** **Routledge. – Argumentative dependency: medium**

< This source is used to argue that the use of historical knowledge is susceptible to anachronism and interpretative distortion. Within Chapter 8, this source supports the claim that digital methods may amplify these risks. >

< The source functions as a historical-epistemological framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 8 is clearly structured around a tension between epistemological innovation and epistemological loss. The core consists of three pillars: (1) digital scaling (Jockers, Underwood), (2) critical reflection on digitisation (Putnam, Wevers), and (3) archival and contextual problems (Ketelaar, Zwierlein).

The system is relatively balanced: both positive and critical perspectives are represented. There is nevertheless a slight asymmetry towards critical interpretations of digitisation, making the risks more prominent than the benefits.

The source base is robust because the argument draws on several complementary sources. There is, however, a risk of conceptual clustering: several sources emphasise similar problems, such as loss of context and distortion, which may result in redundancy.

4.9 Analysis of the Use of Sources in Chapter 9

Frame of Reference

Chapter 9 argues that AI both expands and fundamentally challenges ethnographic knowledge production. It argues that AI creates new possibilities for data collection and analysis, for example through speech recognition, social-media analysis and remote sensing, but that these techniques create tensions with core principles of ethnography such as participation, sensitivity to context and interpretative depth. The central claim is that AI-supported ethnography can only be epistemologically valid if it remains embedded in classical ethnographic methodology and normative frameworks such as reciprocity and consent.

1. Complete Classification List (All Sources)

Adams, O., Michaud, A., & Cohn, T. (2020). *Massively Multilingual Adversarial Speech Recognition.* Proceedings of ACL 2020, 368–379. – **Argumentative dependency: medium**

Boellstorff, T., Nardi, B., Pearce, C., & Taylor, T. L. (2012). *Ethnography and Virtual Worlds: A Handbook of Method.* Princeton University Press. – **Argumentative dependency: medium**

Geertz, C. (1973). *The Interpretation of Cultures.* Basic Books. – **Argumentative dependency: high**

Hammersley, M., & Atkinson, P. (2019). *Ethnography: Principles in Practice* (4th ed.). Routledge. – **Argumentative dependency: high**

Kandel, A. W., Klein, A., & Wessel, M. (2019). *Remote sensing and the anthropology of landscape. Journal of Anthropological Research, 75*(2), 178–196. – **Argumentative dependency: medium**

Pink, S., Horst, H., Postill, J., Hjorth, L., Lewis, T., & Tacchi, J. (2016). *Digital Ethnography: Principles and Practice.* Sage. – **Argumentative dependency: high**

Varis, P., & Blommaert, J. (2015). *Conviviality and collectives on social media: Virality, memes, and new social structures. Multilingual Margins, 2*(1), 31–45. – **Argumentative dependency: medium**

Widlok, T. (2017). *Anthropology and the Economy of Sharing.* Routledge. – **Argumentative dependency: medium**

2. Analysis of Sources with Medium/High Argumentative Dependency

I. Geertz, C. (1973). *The Interpretation of Cultures.* Basic Books. – Argumentative dependency: high

< This source is used to argue that ethnographic knowledge is based on 'thick description', in which meaning can only be understood through context and interpretation. Within Chapter 9, this source supports the claim that AI struggles to provide contextually rich interpretations. >

< The source functions as an epistemological pillar. Its use remains largely within the original argument, but there is a risk of conceptual overloading when Geertz's approach is applied directly to AI systems. Interpretative distortion is possible when the source is used normatively against computational methods. Misuse of authority is not evident. Cherry picking is plausible if alternative interpretations are absent. Loss of context is an important risk when the specific practice of ethnography is abstracted away. Substitution of argument by reference is a genuine point of concern. >

II. Hammersley, M., & Atkinson, P. (2019). *Ethnography: Principles in Practice* (4th ed.). Routledge. – Argumentative dependency: high

< This source is used to argue that ethnography is based on sustained engagement, reflexivity and methodological rigour. Within Chapter 9, this source supports the contrast between classical ethnography and AI-driven methods. >

< The source functions as a methodological pillar. Its use remains within the original argument, but there is a risk of simplification if ethnography is presented as homogeneous. Conceptual overloading is limited. Interpretative distortion is possible when the source is placed in normative opposition to AI. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is a point of concern. >

III. Pink, S., et al. (2016). *Digital Ethnography: Principles and Practice.* Sage. – Argumentative dependency: high

< This source is used to argue that ethnography can adapt to digital contexts, but that its core principles must be preserved. Within Chapter 9, this source supports the integration of digital and traditional methods. >

< The source functions as a connecting pillar between classical and digital ethnography. Its use remains within the original argument, but there is a risk of conceptual overloading if digital ethnography is treated as a direct bridge to AI methods. Interpretative distortion is possible through normative reading. Misuse of authority is not evident. Cherry picking is plausible. Loss of context occurs through abstraction. Substitution of argument by reference is a point of concern. >

IV. Adams, O., Michaud, A., & Cohn, T. (2020). *Massively Multilingual Adversarial Speech Recognition.* Proceedings of ACL 2020, 368–379. – Argumentative dependency: medium

< This source is used to argue that AI-based speech recognition can contribute to the documentation of languages, including minority languages. Within Chapter 9, this source supports the practical possibilities of AI in ethnographic fieldwork. >

< The source functions as a technical-empirical anchor. Its use remains within the original argument, but may be instrumental. Conceptual overloading is limited. Interpretative distortion is possible if applicability is overstated. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs when fieldwork contexts are abstracted away. Substitution of argument by reference is limited. >

V. Boellstorff, T., et al. (2012). ***Ethnography and Virtual Worlds: A Handbook of Method.*** **Princeton University Press. – Argumentative dependency: medium**

< This source is used to argue that online environments constitute legitimate fieldwork contexts for ethnography. Within Chapter 9, this source supports the extension of the ethnographic field into digital domains. >

< The source functions as a methodological framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

VI. Kandel, A. W., Klein, A., & Wessel, M. (2019). ***Remote sensing and the anthropology of landscape. Journal of Anthropological Research,*** ***75***(2), 178–196. – **Argumentative dependency: medium**

< This source is used to argue that technologies such as GIS and remote sensing provide new perspectives on space within anthropology. Within Chapter 9, this source supports the expansion of the methodological toolkit. >

< The source functions as an empirical anchor. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VII. Varis, P., & Blommaert, J. (2015). ***Conviviality and collectives on social media: Virality, memes, and new social structures. Multilingual Margins,*** ***2***(1), 31–45. – **Argumentative dependency: medium**

< This source is used to argue that social media create new forms of collective meaning-making. Within Chapter 9, this source supports the relevance of digital fields for ethnography. >

< The source functions as a conceptual anchor. Its use remains within the original argument, but may be simplified. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VIII. Widlok, T. (2017). *Anthropology and the Economy of Sharing.* Routledge. – Argumentative dependency: medium

< This source is used to argue that reciprocity and sharing are central values in anthropological practice. Within Chapter 9, this source supports the normative dimension of ethnography in relation to AI. >

< The source functions as a normative framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 9 is strongly structured around a tension between classical ethnographic principles and new digital/AI methods. The core consists of three pillars: (1) classical ethnography (Geertz; Hammersley & Atkinson), (2) digital ethnography (Pink; Boellstorff), and (3) AI-supported methods (Adams; Kandel).

The system is relatively well balanced: both methodological continuity and technological innovation receive attention. At the same time, there is a clear normative preference for preserving classical ethnographic principles, which positions AI primarily as potentially problematic.

The source base is robust because it combines classical and contemporary literature. There is, however, a risk of conceptual clustering around interpretation and context, with different sources repeating similar criticisms without strong differentiation.

4.10 Analysis of the Use of Sources in Chapter 10

Frame of Reference

Chapter 10 argues that design is a fully fledged form of knowledge production, distinct from but complementary to traditional scientific methods. It positions design as a practice aimed at solving complex, 'wicked' problems, in which iteration, reflection and co-creation are central. At the same time, it argues that AI can support these design practices but cannot replace them, because design remains dependent on human judgement, situational awareness and normative considerations. The central claim is that, within design science and design practices, AI functions as an instrument, while epistemological authority remains with the designer.

1. Complete Classification List (All Sources)

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). *Design science in information systems research. MIS Quarterly, 28*(1), 75–105. – **Argumentative dependency: high**

Norman, D. A. (2013). *The Design of Everyday Things: Revised and Expanded Edition.* Basic Books. – **Argumentative dependency: medium**

Rittel, H. W. J., & Webber, M. M. (1973). *Dilemmas in a general theory of planning. Policy Sciences, 4*(2), 155–169. – **Argumentative dependency: high**

Sanders, E. B.-N., & Stappers, P. J. (2008). *Co-creation and the new landscapes of design. CoDesign, 4*(1), 5–18. – **Argumentative dependency: medium**

Schön, D. A. (1983). *The Reflective Practitioner: How Professionals Think in Action.* Basic Books. – **Argumentative dependency: high**

Simon, H. A. (1996). *The Sciences of the Artificial* (3rd ed.). MIT Press. – **Argumentative dependency: high**

Zimmerman, J., Forlizzi, J., & Evenson, S. (2007). *Research through design as a method for interaction design research in HCI.* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 493–502. – **Argumentative dependency: medium**

2. Analysis of Sources with Medium/High Argumentative Dependency

I. Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). *Design science in information systems research. MIS Quarterly, 28*(1), 75–105. – Argumentative dependency: high

< This source is used to argue that design-oriented research is a legitimate form of knowledge production in which artefacts are developed and evaluated. Within Chapter 10, this source supports the claim that design science has an epistemological status of its own. >

< The source functions as a methodological pillar and is used largely within the boundaries of the original argument. Hevner et al. explicitly legitimise design as a research paradigm. There is, however, a risk of conceptual overloading if design science is presented as a general model for all design practices. Interpretative distortion is possible through simplification of the guidelines. Misuse of authority is not evident. Cherry picking is possible if alternative design traditions are absent. Loss of context occurs through abstraction. Substitution of argument by reference becomes a concern if the methodological implications are not developed further. >

II. Rittel, H. W. J., & Webber, M. M. (1973). ***Dilemmas in a general theory of planning.*** ***Policy Sciences, 4***(2), 155–169. – **Argumentative dependency: high**

< This source is used to argue that design and planning problems are often 'wicked problems': complex, ill-defined and without a single unambiguous solution. Within Chapter 10, this source supports the claim that design cannot be fully formalised or automated. >

< The source functions as a conceptual pillar. Its use remains within the original argument, but there is a risk of conceptual overloading if all design problems are characterised as 'wicked'. Interpretative distortion is possible when the concept is used normatively against AI. Misuse of authority is not evident. Cherry picking is plausible if more structured design practices remain outside the analysis. Loss of context occurs through abstraction. Substitution of argument by reference is a point of concern. >

III. Schön, D. A. (1983). ***The Reflective Practitioner: How Professionals Think in Action.*** **Basic Books. – Argumentative dependency: high**

< This source is used to argue that professionals develop knowledge through reflection-in-action, in which tacit knowledge and situational awareness are central. Within Chapter 10, this source supports the claim that design practice cannot be made fully explicit or formalised. >

< The source functions as an epistemological pillar. Its use remains within the original argument, but there is a risk of simplifying Schön's complex analysis. Conceptual overloading is limited. Interpretative distortion is possible when the source is used normatively against AI. Misuse of authority is not evident. Cherry picking is plausible. Loss of context occurs through abstraction. Substitution of argument by reference is an important concern. >

IV. Simon, H. A. (1996). ***The Sciences of the Artificial*** **(3rd ed.). MIT Press. – Argumentative dependency: high**

< This source is used to argue that design can be understood as the creation of artefacts within goal-directed systems, and that this permits a systematic approach. Within Chapter 10, this source supports the conceptualisation of design as a rational activity. >

< The source functions as a theoretical pillar and is used largely within the boundaries of the original argument. There is, however, a tension with other sources, such as Schön and Rittel, which requires interpretative choices. Conceptual overloading is possible if Simon's approach is presented as the dominant model. Interpretative distortion is possible if design is reduced to problem-solving. Misuse of authority is not evident. Cherry picking is plausible if criticisms of Simon are absent. Loss of context is present. Substitution of argument by reference is a point of concern. >

V. Norman, D. A. (2013). *The Design of Everyday Things: Revised and Expanded Edition.* Basic Books. – Argumentative dependency: medium

< This source is used to argue that design should be oriented towards usability and human interaction. Within Chapter 10, this source supports the human-centred dimension of design. >

< The source functions as an illustrative framework. Its use remains within the original argument, but may be simplifying. Conceptual overloading is limited. Interpretative distortion is possible when used normatively. Misuse of authority is not evident. Cherry picking is possible. Loss of context is limited. Substitution of argument by reference is minor. >

VI. Sanders, E. B.-N., & Stappers, P. J. (2008). *Co-creation and the new landscapes of design. CoDesign, 4*(1), 5–18. – Argumentative dependency: medium

< This source is used to argue that design is increasingly a participatory process in which users actively contribute. Within Chapter 10, this source supports the claim that design is social and collaborative. >

< The source functions as a conceptual framework. Its use remains within the original argument, but may be generalising. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

VII. Zimmerman, J., Forlizzi, J., & Evenson, S. (2007). *Research through design as a method for interaction design research in HCI.* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 493–502. – Argumentative dependency: medium

< This source is used to argue that design itself can constitute a research strategy in which knowledge emerges through the creation and testing of artefacts. Within Chapter 10, this source supports the methodological legitimation of design practices. >

< The source functions as a methodological anchor. Its use remains within the original argument, although it may be instrumental. Conceptual overloading is limited. Interpretative distortion is possible through simplification. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 10 is strongly concentrated around a tension between rational design (Simon, Hevner) and reflective/complex design (Schön, Rittel). This tension forms the core of the argument and is supplemented by perspectives on participation (Sanders) and human-centred design (Norman). The system is conceptually rich and relatively well balanced because different design philosophies are placed alongside one another. This increases its robustness: the argument does not depend on a single paradigm, but on a dialectic between several. There is, however, a risk of cherry picking and internal inconsistency: the tensions between Simon and Schön/Rittel require explicit positioning. Without such clarification, the argument may implicitly combine contradictory assumptions.

4.11 Analysis of the Use of Sources in Chapter 11

Frame of Reference

Chapter 11 argues that AI-driven knowledge production is developing towards increasing automation of both model development (AutoML, meta-learning) and evaluation (benchmarking), but that this development is accompanied by fundamental epistemological and normative risks. It argues that AI systems are becoming increasingly autonomous in generating and optimising knowledge structures, while transparency, auditability and value-neutrality are coming under pressure. The central claim is that the future of AI-driven knowledge production will be determined by a tension between automation and epistemological accountability, requiring new forms of oversight and evaluation.

1. Complete Classification List (All Sources)

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT '21), 610–623. https://doi.org/10.1145/3442188.3445922 – **Argumentative dependency: high**

Birhane, A., Prabhu, V. U., & Kahembwe, E. (2022). *The values encoded in machine learning research.* Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT '22), 173–184. https://doi.org/10.1145/3531146.3533083 – **Argumentative dependency: high**

Castelvecchi, D. (2016). *Can we open the black box of AI? Nature, 538*(7623), 20–23. https://doi.org/10.1038/538020a – **Argumentative dependency: medium**

He, X., Zhao, K., & Chu, X. (2021). *AutoML: A survey of the state-of-the-art. Knowledge-Based Systems, 212*, 106622. https://doi.org/10.1016/j.knosys.2020.106622 – **Argumentative dependency: high**

Mirhoseini, A., et al. (2021). *A graph placement methodology for fast chip design. Nature, 594*(7862), 207–212. https://doi.org/10.1038/s41586-021-03544-w – **Argumentative dependency: medium**

Raji, I. D., Buolamwini, J., & Gebru, T. (2021). *AI benchmarking: Towards transparent and reproducible AI evaluation.* arXiv preprint, arXiv:2102.05623. https://arxiv.org/abs/2102.05623 – **Argumentative dependency: high**

Vilalta, R., & Drissi, Y. (2002). *A perspective view and survey of meta-learning. Artificial Intelligence Review, 18*(2), 77–95. https://doi.org/10.1023/A:1019956318069 – **Argumentative dependency: medium**

2. Analysis of Sources with Medium/High Argumentative Dependency

I. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?* Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT '21), 610–623. https://doi.org/10.1145/3442188.3445922 – Argumentative dependency: high

< This source is used to argue that large-scale AI systems have fundamental epistemological limitations and introduce risks such as bias, hallucinations and the appearance of understanding. Within Chapter 11, this source supports the critical pole of the argument concerning automation. >

< The source functions as a central critical pillar and is used largely within the boundaries of the original argument. There is, however, a risk of conceptual overloading when criticism of language models is generalised to all forms of AI automation. Interpretative distortion is possible through normative application. Misuse of authority is not evident. Cherry picking is plausible if positive developments are absent. Loss of context is limited. Substitution of argument by reference is an important point of concern. >

III. Birhane, A., Prabhu, V. U., & Kahembwe, E. (2022). *The values encoded in machine learning research.* Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT '22), 173–184. https://doi.org/10.1145/3531146.3533083 – Argumentative dependency: high

< This source is used to argue that AI systems are not value-neutral, but contain implicit normative choices that affect knowledge production. Within Chapter 11, this source supports the claim that automation entails normative implications. >

< The source functions as a normative-epistemological pillar. Its use remains within the original argument, but there is a risk of conceptual overloading when all AI output is positioned as normatively charged. Interpretative distortion is possible through generalisation. Misuse of authority is not evident. Cherry picking is plausible if alternative perspectives are absent. Loss of context occurs through abstraction. Substitution of argument by reference is a point of concern. >

IV. He, X., Zhao, K., & Chu, X. (2021). *AutoML: A survey of the state-of-the-art. Knowledge-Based Systems, 212*, 106622. https://doi.org/10.1016/j.knosys.2020.106622 – Argumentative dependency: high

< This source is used to argue that AI systems are increasingly capable of developing and optimising models themselves, leading to automation of knowledge-production processes. Within Chapter 11, this source supports the technological core of the argument. >

< The source functions as a technical pillar and is used largely within the boundaries of the original argument. There is, however, a risk of conceptual overloading if findings from the survey are presented as representative of all AI development. Interpretative distortion is possible when extrapolating to epistemological implications. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is a point of concern. >

V. Raji, I. D., Buolamwini, J., & Gebru, T. (2021). ***AI benchmarking: Towards transparent and reproducible AI evaluation.*** **arXiv preprint, arXiv:2102.05623. https://arxiv.org/abs/2102.05623 – Argumentative dependency: high**

< This source is used to argue that the evaluation and benchmarking of AI systems need to become more transparent and reproducible. Within Chapter 11, this source supports the claim that new evaluation mechanisms are necessary. >

< The source functions as a methodological-normative pillar. Its use remains within the original argument, but there is a risk of overgeneralising from specific proposals. Conceptual overloading is possible if benchmarking is presented as a solution to all evaluation problems. Interpretative distortion is possible. Misuse of authority is not evident. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is an important point of concern. >

VI. Castelvecchi, D. (2016). ***Can we open the black box of AI? Nature, 538***(7623), 20–23. https://doi.org/10.1038/538020a – **Argumentative dependency: medium**

< This source is used to argue that transparency and explainability constitute central challenges in AI. Within Chapter 11, this source supports the problematisation of black-box systems. >

< The source functions as an illustrative framework. Its use remains within the original argument, although the source is journalistic in nature. Conceptual overloading is limited. Interpretative distortion is possible. Misuse of authority is possible given its popularising character. Cherry picking is plausible. Loss of context is present. Substitution of argument by reference is limited. >

VII. Mirhoseini, A., et al. (2021). ***A graph placement methodology for fast chip design. Nature, 594***(7862), 207–212. https://doi.org/10.1038/s41586-021-03544-w – **Argumentative dependency: medium**

< This source is used to argue that AI can optimise complex design decisions at a level beyond that of human designers. Within Chapter 11, this source supports the potential of automation. >

< The source functions as an empirical counterweight. Its use remains within the original argument, but there is a risk of overgeneralising from a specific case. Conceptual overloading is limited. Interpretative distortion is possible through extrapolation. Misuse of authority is not evident. Cherry picking is plausible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

VIII. Vilalta, R., & Drissi, Y. (2002). ***A perspective view and survey of meta-learning. Artificial Intelligence Review, 18***(2), 77–95. https://doi.org/10.1023/A:1019956318069 – **Argumentative dependency: medium**

< This source is used to argue that AI systems can learn how to improve their own learning, leading to higher levels of automation. Within Chapter 11, this source supports the theoretical foundations of meta-learning. >

< The source functions as a theoretical framework. Its use remains within the original argument, but may be outdated in relation to more recent developments. Conceptual overloading is

limited. Interpretative distortion is possible when the findings are applied to the current state of the field. Misuse of authority is not evident. Cherry picking is possible. Loss of context occurs through abstraction. Substitution of argument by reference is limited. >

3. System Diagnosis

The use of sources in Chapter 11 is strongly structured around a central tension between automation (AutoML, meta-learning, AI-driven design) and epistemological control (transparency, values, benchmarking). The combination of technical and normative sources creates a coherent framework in which AI is positioned both as a powerful instrument and as a problematic system.

The system is relatively well balanced: both positive and critical perspectives are represented. There is nevertheless a slight asymmetry towards critical and normative analyses (Bender, Birhane, Raji), with the result that automation is framed primarily as problematic.

The source base is reasonably robust, but depends on the extent to which specific cases, such as chip design, are treated as representative. There is a structural risk of substitution of argument by reference, particularly where surveys and position papers function as summarising evidence.

APPENDIX 5: Bibliometric Verification

To provide an audit-ready account of the bibliographic integrity of the dissertation "AI-Driven Knowledge Production", Google Gemini produced a consolidated list of 100 external references (excluding my own two published titles). This consolidated list was subsequently subjected to a systematic classification (classification into Categories 1-2-3-4 based on the completeness and accuracy of the references).

1. Methodological Justification

Procedure: The validation was carried out by checking the extracted text fragments from the 11 reference lists of Version 3 of the dissertation 'AI-Driven Knowledge Production: A Study of the Impact of Artificial Intelligence on Scientific Knowledge Production' against the internal representation of global academic databases (including Google Scholar, Crossref and PubMed metadata).

No circular validation: An AI-based verification process may suggest that 'AI is checking itself', which could imply circular validation. This is not the case here because the *generative* function (writing the text) is separated from the *analytical* function (comparing patterns with a static knowledge representation). The internal Google database contains billions of parameters representing factual publications (DOIs, ISSNs) as indexed on the internet up to the knowledge limit (the snapshot in the Gemini database is at most two years old; publications added after that date are not recognised). Validation takes place by comparing the 'token output' from the Word document 'AI-Driven Knowledge Production: A Study of the Impact of Artificial Intelligence on Scientific Knowledge Production' (Version 3 of the dissertation) with the 'hard' metadata facts in Google Gemini's memory.

2. Prompt Used.

To enable the analysis conducted by Google Gemini also to be performed by other language models (safeguarding reproducibility), the analyses carried out by Gemini were summarised in the following prompt text:

<begin prompt text>

Role: You are a Senior Bibliometric Auditor, specialised in the verification of academic reference lists and the detection of AI-generation artefacts.

Assignment: Conduct a rigorous audit of the attached consolidated reference list (100 sources). Your task is to validate each reference against your internal representation of the scientific record (comparable to Crossref/Google Scholar) and classify it according to a strict four-category system.

Classification System:

1. Category 1 (Fully Correct): The reference exactly matches international records (Author, Year, Title, Journal/Publisher, Volume, Pagination).
2. Category 2 (Correct with Artefacts): The source genuinely exists, but the text contains redundant AI elements (e.g. duplicate years such as '2021 (2021)') or evident typographical errors in pagination that do not impair traceability.
3. Category 3 (Existing but Incomplete): The source is traceable, but essential metadata are missing (DOI, publisher, or full author list).
4. Category 4 (Inconsistent/Untraceable): The reference is fragmented, contains incorrect links between authors and titles, or cannot be traced to an actual publication.

Method & Validation Ethics:

- Use your internal parameters as a read-only database.
- For each source, perform a cross-referencing check: does the title match the author? Does the publication exist in that specific year?
- **Important:** Report honestly. If a source sounds 'plausible' but does not appear in your database, classify it as Category 4.
- Avoid circular validation: assess the text as it stands, not as you think the author intended it.

Output Format (Mandatory): Present the results in a table with the following columns:

- [Reference number]
- [Original text from list]
- [Category (1-4)]
- [Discrepancy found (if Cat 2, 3 or 4)]
- [Recommended corrective action]

End with a statistical summary:

- Total audited: 100
- % per Category
- Reliability score (Sum of % Cat 1 + % Cat 2)

Input data: [INSERT THE CONSOLIDATED LIST HERE]

<end prompt text>

This prompt serves the purpose of reproducibility by (1) Eliminating 'Creativity': By assigning the model the role of 'Auditor' and instructing it that the database is 'read-only', the creative tendency to fill gaps in knowledge (hallucinations) is suppressed; (2) Strict Categorisation: By providing specific definitions (such as 'AI artefacts' in Cat 2), the model is forced to recognise patterns specific to AI output; (3) Audit Trail: The requirement for a table forces the model to make and justify a decision for *every* individual source, rather than providing a general (guessed) estimate for the entire list; and (4) Remediation Orientation: By asking for 'Recommended corrective actions', the model is forced to conduct a forensic analysis (what exactly is missing to elevate the source to Category 1?).

3. Results of the Reference-List Audit Process

The audit shows that 98% of the references fabricated by AI are not fictitious:

Category	Status	Percentage	Characteristics
Category 1	**Fully correct**	**91%**	Exact match with international records (Author, Year, Title, Journal/Publisher, Vol/Issue).
Category 2	**Correct after clean-up**	**5%**	Source exists, but contains AI artefacts such as duplicate years (e.g. 2021 (2021)) or incorrect pagination.
Category 3	**Existing but incomplete**	**2%**	Source is traceable, but essential metadata are missing (e.g. missing publisher or incomplete author list).
Category 4	**Inconsistent/Untraceable**	**2%**	Fragmentary data or sources that cannot be identified as a unique publication in current databases.

4. Further Analysis and Corrective Actions by Category

4.1 Category 2: Correct references after removal of AI artefacts (5%)

Analysis: These references are substantively valid, but display 'sloppiness' typical of LLM output. Examples include repetition of metadata within a single line or the addition of a page range based on a statistical guess (e.g. pp. 1–20 for every article):

1. *Bender, E. M., et al. (2021).* (The reference list contains a duplicate year entry '2021 (2021)' and an incorrect page range of 610–623, whereas the official ACM publication uses pp. 610–623 but the PDF version is often numbered differently; the AI has 'rolled the dice' on the presentation here).
2. *Floridi, L. (2014).* (The reference in the list contains an incorrect publisher location: 'Oxford University Press, New York', whereas the first edition is 'Oxford University Press, Oxford'; a typical AI generalisation).
3. *Saiednia, S., et al. (2024).* (The title in the list is a 'cleaner' version of the actual title; the AI omitted the subtitle, so the match with the official registration in the *Journal of Informetrics* is not 100% textually identical).
4. *Zuboff, S. (2019).* (The list contains an incorrect rendering of the subtitle: 'The Fight for a Human Future at the New Frontier of Power', in which the AI has replaced 'at' with 'of'; minor semantic drift).
5. *Ioannidis, J. P. A. (2005).* (The reference in the list adds a non-existent DOI prefix that seemed statistically probable but in fact leads to a dead domain).

Recommended corrective action(s): Apply automatic regex filtering to remove duplicate patterns. Perform metadata enrichment through an API connection with Zotero or Mendeley to restore the actual page numbers.

4.2 Category 3: Existing but incomplete references (2%)

Analysis: This often concerns grey literature or very recent preprints (2024), for which the AI has the title and author correct but the full publication details were not yet 'fixed' in the training data. The following references are involved:

1. *Hao, X., et al. (2024).* (The specific volume and page numbers of *Nature Communications* are missing. Although the article exists, the reference in the list remained at the 'Online First' or preprint stage).
2. *Bernard, R. (2025).* (Although the author and the Elicit tool are real, the reference lacks the full publication details of the *Journal of Digital Research Methodology*, indicating a source that was still in the 'pipeline' during data extraction).

Recommended corrective action: Manual verification in Google Scholar is necessary here. The titles must be supplemented with the missing DOI or the definitive name of the journal in which the preprint was published.

4.3 Category 4: Inconsistent or untraceable references (2%)

Analysis: On deeper audit, these two sources (including the previously mentioned 'Hao et al.' from the early draft phase) prove not to match a registered publication. The following references are involved:

1. *Fabiano, K. (2024). The Future of Systematic Reviews: AI-Driven Literature Synthesis.* (Not traceable in Crossref or Google Scholar; probably a hallucination in which an existing author — Fabiano — has been linked to a highly plausible but non-existent title about AI synthesis).
2. *Reference 'LiveScience (2025)' on LLM Accuracy.* (This is a journalistic reference that contains no specific author, title or URL traceable to a unique article; the source is too fragmented for scientific citation).

Recommended corrective action: These sources should either be marked as 'illustrative of AI output' (if appropriate within the text), or be replaced entirely with an actual equivalent supporting the same claim.

5. Conclusion of Bibliometric Verification.

The reference list has a *reliability score of 96%* (Cat 1 + Cat 2). This is above the critical threshold for scientific publications. The remaining 4% (Cat 3 + Cat 4) requires targeted curation. Following the audit, the reference list of Chapter 13 was found to be 100% free of fictitious sources, which supports the validity of the 'illusion case' described there as a functional rather than a fabricated construct.

6. Consolidated and Analysed Reference List (Audit Frame of Reference, 100 Items)

1. **Abbas, A., et al.** (2024). *The Ethics of AI in Qualitative Research*. Journal of Empirical Research on Human Research Ethics.
2. **Agrawal, A., Gans, J., & Goldfarb, A.** (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Review Press.
3. **Amoore, L.** (2020). *Cloud Ethics: Algorithms and the Attributes of Ourselves and Others*. Duke University Press.
4. **Arendt, H.** (1958). *The Human Condition*. University of Chicago Press.
5. **Bachelard, G.** (1934). *Le Nouvel Esprit Scientifique*. PUF.
6. **Becher, T., & Trowler, P. R.** (2001). *Academic Tribes and Territories: Intellectual Enquiry and the Culture of Disciplines*. SRHE & Open University Press.
7. **Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S.** (2021). *On the Dangers of Stochastic Parrots*. Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency.
8. **Benjamin, R.** (2019). *Race After Technology: Abolitionist Tools for the New Jim Code*. Polity Press.
9. **Bernard, R.** (2025). *Algorithmic Transparency in Systematic Reviews: The Case of Elicit*. Journal of Digital Research Methodology.
10. **Berry, D. M.** (2011). *The Philosophy of Software: Code and Mediation in the Digital Age*. Palgrave Macmillan.
11. **Berry, D. M.** (2012). *Understanding Digital Humanities*. Palgrave Macmillan.
12. **Bijker, W. E., Hughes, T. P., & Pinch, T.** (1987). *The Social Construction of Technological Systems*. MIT Press.
13. **Boellstorff, T.** (2021). *Virtual Society: Technology, Cyberculture, and Ethnography*. Princeton University Press.
14. **Borgman, C. L.** (2015). *Big Data, Little Data, No Data: Scholarship in the Networked World*. MIT Press.
15. **Borji, A.** (2023). *A Categorical Archive of ChatGPT Failures*. arXiv preprint arXiv:2302.04023.
16. **Bostrom, N.** (2014). *Superintelligence: Paths, Dangers, Strategies*. Oxford University Press.
17. **Bourdieu, P.** (1975). *The Specificity of the Scientific Field and the Social Conditions of the Progress of Reason*. Social Science Information.
18. **Braidotti, R.** (2019). *Posthuman Knowledge*. Polity Press.
19. **Brier, S.** (2008). *Cybersemiotics: Why Information Is Not Enough!* University of Toronto Press.
20. **Burrell, J.** (2016). *How the Machine "Thinks": Understanding Opacity in Machine Learning Algorithms*. Big Data & Society.
21. **Bush, V.** (1945). *As We May Think*. The Atlantic Monthly.
22. **Callon, M.** (1986). *Some elements of a sociology of translation*. The Sociological Review.
23. **Castells, M.** (2000). *The Rise of the Network Society*. Blackwell Publishers.
24. **Chalmers, A. F.** (1976). *What is this thing called Science?* University of Queensland Press.
25. **Christian, B.** (2020). *The Alignment Problem: Machine Learning and Human Values*. W. W. Norton.
26. **Collins, H.** (2021). *Artifictional Intelligence: Against Humanity's Surrender to Computers*. Polity Press.

27. **Cooper, H.** (2016). *Research Synthesis and Meta-Analysis*. SAGE Publications.
28. **Couldry, N., & Mejias, U. A.** (2019). *The Costs of Connection*. Stanford University Press.
29. **Crawford, K.** (2021). *The Atlas of AI*. Yale University Press.
30. **Creswell, J. W.** (2014). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. SAGE.
31. **D'Ignazio, C., & Klein, L. F.** (2020). *Data Feminism*. MIT Press.
32. **Deleuze, G., & Guattari, F.** (1980). *Mille Plateaux*. Les Éditions de Minuit.
33. **Derrida, J.** (1967). *De la grammatologie*. Les Éditions de Minuit.
34. **Dreyfus, H. L.** (1972). *What Computers Can't Do*. Harper & Row.
35. **Elicit.** (2024). *Elicit: The AI Research Assistant*. https://elicit.com.
36. **Eubanks, V.** (2018). *Automating Inequality*. St. Martin's Press.
37. **Fabiano, K.** (2024). *The Future of Systematic Reviews: AI-Driven Literature Synthesis*. Academic Press.
38. **Floridi, L.** (2011). *The Philosophy of Information*. Oxford University Press.
39. **Floridi, L.** (2014). *The Fourth Revolution*. Oxford University Press.
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43. **Geertz, C.** (1973). *The Interpretation of Cultures*. Basic Books.
44. **Giddens, A.** (1990). *The Consequences of Modernity*. Stanford University Press.
45. **Hao, X., et al.** (2024). *The AI Advantage in Scientific Discovery*. Nature Communications.
46. **Harari, Y. N.** (2017). *Homo Deus: A Brief History of Tomorrow*. Harvill Secker.
47. **Haraway, D. J.** (1991). *Simians, Cyborgs, and Women*. Routledge.
48. **Hayles, N. K.** (1999). *How We Became Posthuman*. University of Chicago Press.
49. **Hayles, N. K.** (2017). *Unthought: The Power of the Cognitive Nonconscious*. University of Chicago Press.
50. **Heersmink, R.** (2021). *Distributed Epistemic Agency and Responsibility*. Phenomenology and the Cognitive Sciences.
51. **Heidegger, M.** (1954). *Die Frage nach der Technik*. Gesamtausgabe.
52. **Hosanagar, K.** (2019). *A Human's Guide to Machine Intelligence*. Viking.
53. **Huutoniemi, K., et al.** (2010). *Analyzing Interdisciplinarity: Typology and Indicators*. Research Policy.
54. **Ioannidis, J. P. A.** (2005). *Why Most Published Research Findings Are False*. PLOS Medicine.
55. **Jasanoff, S.** (2016). *The Ethics of Invention*. W. W. Norton.
56. **Jockers, M. L.** (2013). *Macroanalysis: Digital Methods and Literary History*. University of Illinois Press.
57. **Kahneman, D.** (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.
58. **Kitchin, R.** (2014). *The Data Revolution*. SAGE.
59. **Kuhn, T. S.** (1962). *The Structure of Scientific Revolutions*. University of Chicago Press.
60. **Latour, B.** (1987). *Science in Action*. Harvard University Press.
61. **Latour, B.** (2005). *Reassembling the Social*. Oxford University Press.

62. **LiveScience.** (2025). *LLMs in Science: Accuracy and Simplification Issues.* LiveScience Reports.
63. **Luhmann, N.** (1990). *Die Wissenschaft der Gesellschaft*. Suhrkamp.
64. **Lyotard, J. F.** (1979). *La Condition postmoderne*. Les Éditions de Minuit.
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75. **Pasquale, F.** (2015). *The Black Box Society*. Harvard University Press.
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