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An Automatic Reproducibility Checking Pipeline for the Learning Analytics Academic Community

Bachelorarbeit

im Studiengang Informatik

von

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Hannover, den 12.09.2025

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Domenik Kern

Abstract

Reproducibility in research is essential for ensuring its trustworthiness and transparency. When research cannot be reproduced, its findings cannot be fully trusted. Many studies in the past have failed to be reproduced, leading to what is commonly referred to as the reproducibility crisis. Over the years, various solutions have been proposed, including the adoption of open science practices to improve the situation. However, within the Learning Analytics community, there remains considerable room for improvement, as recent studies have shown, where no studies could be reproduced in a 15-minute time-frame [12].

To help ensure that research adheres to reproducibility guidelines and thereby directly improves its rigor [5], this thesis proposes an automatic reproducibility checking pipeline. The pipeline evaluates research papers using a reproducibility checklist, aided by the Large Language Model Gemma 3. This approach provides an overview of the current state of the 15th Learning Analytics & Knowledge (LAK) Conference by analyzing open science and reproducibility aspects in research papers, and allows comparison with findings from the 13th LAK Conference [12]. Additionally, the pipeline was evaluated through a human study to verify its reliability.

The LAK'25 overview suggests a positive trend in Open Data practices. While approximately 25% of papers in LAK'21/22 shared their data, this figure increased to 33% in 2025. The proportion of papers sharing their code also rose, from 13% to approximately 33%. Despite this progress, substantial room for improvement remains in the sharing of both data and code to better align with Open Science principles and make reproducibility possible.

The study results indicated a positive reception of the tool, with questions on the completeness and helpfulness of the checklist receiving an average rating of 4.71 on a 5-point Likert scale. The prototype was also positively received for its effectiveness in identifying reproducibility criteria. However, it seems to not be a reliable evaluator on its own, as it sometimes diverges from manual evaluations and tends to produce superficial assessments, especially in sections such as Methods or Results.

Contents

Chapter 1

Introduction

Learning Analytics, a prominent subfield of educational technology, has experienced significant growth since its formal emergence in 2011. The field focuses on leveraging data to improve both teaching and learning processes through methods such as visualization, recommendations, and other data-driven innovations [24]. This growth is reflected in the increasing interest from the research community, as seen in the record-breaking number of full paper submissions at the 15th International Conference on Learning Analytics and Knowledge (LAK) [24]. However, as the field matures, so too does the need for ensuring the trustworthiness, transparency, and scientific validity of its research outputs. All of these aspects are encompassed by reproducibility, a fundamental cornerstone of high-quality research.

1.1 Problem Statement

More than a decade ago, the term reproducibility crisis emerged in response to concerning findings across various scientific disciplines showing that many research results could not be reliably reproduced [10]. As a countermeasure, the Open Science movement proposed and promoted practices aimed at increasing transparency, accountability, and reproducibility in research [10]. The degree to which these practices have been adopted in the Learning Analytics and Knowledge (LAK) community was examined in a study from 2023, which analyzed papers from LAK'21 and LAK'22 [12]. The findings were disappointing, indicating that reproducibility and adherence to Open Science principles remain limited within the field [12]. Verifying reproducibility can serve as an important quality check and lead to methodological improvements, which in turn can support more reliable decision-making. Despite its importance, there is currently no automated way to assess reproducibility at scale, making it difficult for the community to identify and address shortcomings efficiently.

1.2 Research Objective

This thesis aims to explore how reproducibility in Learning Analytics research can be assessed more effectively using emerging technologies. Specifically, it investigates the potential of Large Language Models (LLMs) to support the automated evaluation of reproducibility in research. LLMs have shown promise in various text analysis tasks and may significantly reduce the time and effort needed to assess complex academic texts. To this end, I propose an automated reproducibility checking pipeline that utilizes an checklist and an LLM to assess the extent to which a research paper addresses key aspects of open science and reproducibility. Additionally, the pipeline is applied to provide an updated overview of the current state of LAK, enabling a comparison to findings from previous years and potentially revealing progress over time.

1.3 Results of the Thesis

Using the pipeline, an overview of the current reproducibility state within the LAK conference proceedings was generated, revealing a positive trend. Similarly, the pipeline itself proved effective in producing a quick overview of research papers, which can significantly support manual evaluations. This potential was also reflected in a small-scale human evaluation of the tool, where it received positive feedback, including from members of the Learning Analytics research community.

1.4 Structure of the Thesis

The structure of this thesis is as follows: Chapter 2 provides the necessary background, introducing the concept of reproducibility, its perceived crisis in research, and the relevance of open science principles. It also presents the Large Language Model (LLM) used in the pipeline. Chapter 3 details the implementation of the pipeline, including the reproducibility checklist and the setup of the human evaluation study. Chapter 4 presents and interprets the results of both the human evaluation and the large-scale analysis of current LAK proceedings. Chapter 5 discusses the findings and outlines the limitations of the pipeline. Finally, Chapter 6 concludes the thesis and highlights directions for future work

Chapter 2

Background

This chapter introduces the key concepts underpinning the later proposed pipeline, including open science, open access, reproducibility, as well as education technology and learning analytics. It also provides a brief overview of natural language processing and large language models, concluding with a description of the Gemma 3 model.

2.1 Open Science

Open Science is a movement aimed at making scientific research, data, and dissemination accessible to all levels of society [5]. It encompasses principles such as transparency, re-use, participation, cooperation, accountability, and reproducibility, with the goal of improving the quality and reliability of research [5]. Open Science practices include open access to publications, data-sharing, open notebooks, transparent research evaluation, reproducible research, and open-source software [5] [22]. The Open Science Taxonomy by Pontika et al. [21] (Figure 2.1) illustrates the broad scope of open science. It is structured into multiple hierarchical levels, where each level provides increasing detail on the different components of open science.

Haim et al. [12] defined key components of Open Science as follows:

- Open Methodology: Details of the methods and evaluation used by the authors, including the setup, logic flow, aggregations of results, etc.
- Open Data: Data that can be freely accessed, reused, and redistributed.
- Open Materials: Sharing research tools, software, and other resources to enable reproducibility.
- Preregistration: Documenting research plans in advance to reduce bias and enhance transparency.

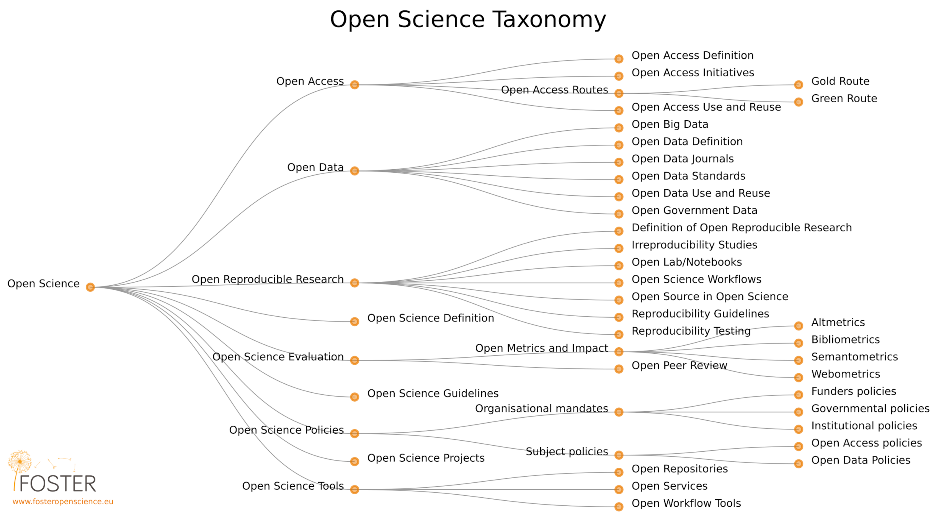


Figure 2.1: The Open Science Taxonomy, Pontika et al. [21].

Both the term open science and the concepts of it are increasing in popularity and usage [22]. It also addresses cultural and systemic challenges, such as aligning scientific norms with values like communality and disinterestedness, as opposed to secrecy and self-interest [10]. By promoting these practices, Open Science aims to create a more inclusive and trustworthy scientific ecosystem [10]. Additionally, it is seen as a catalyst for improving research rigor and fostering cumulative scientific progress [12] and the value of it is accepted by the majority of the scientific community [22].

However, the adoption of Open Science varies across disciplines. For instance, in learning analytics, less than half of the research papers examined at the 13th International Conference on Learning Analytics and Knowledge adhered to key Open Science principles, with only about 5% fully meeting these criteria [12]. Common barriers include a lack of knowledge among researchers and logistical challenges in making datasets, code, and materials openly available [12].

2.1.1 Open Access

As a subset of Open Science practices, Open Access (OA) focuses on the accessibility of scholarly literature by removing price and permission barriers. According to Suber [26], open access refers to the free, online availability of scholarly work with minimal copyright and licensing restrictions. OA significantly increases the potential readership of research and enhances its impact compared to traditional commercial publishing models, which often restrict access [26].

The Association for Computing Machinery (ACM), which also publishes the LAK proceedings, transitioned to an Open Access publishing model in 2025. This shift was motivated by overwhelming support within the computer science community for open access to research [2]. Notably, ACM reported that OA articles are downloaded and cited roughly 70% more frequently than those behind paywalls [2].

By increasing transparency and availability, Open Access also facilitates reproducibility [29].

2.1.2 Open Data and FAIR Principles

The FAIR Principles: Findable, Accessible, Interoperable, and Reusable were introduced to support long-term stewardship, management, and meaningful reuse of scientific data in a digital age [30]. Developed by a coalition of scholars, publishers, and funding bodies, the FAIR framework ensures that both humans and machines can discover, access, reuse data effectively [30]. It allows incremental adoption and domain-specific adaptation, making it practical across diverse scientific disciplines [30]. They are intended as guidelines rather than strict requirements, and it is not necessary to comply with all of them [5] [13]. Over time, these principles have gained broad acceptance across the scientific community [13]. The Open Science Handbook [5] emphasizes the incorporation of the FAIR principles as a way to make data as open as possible. While there is no single definition of Open Data, its central aim is to make non-private and non-confidential data publicly available without restrictions on use [5] [12] [13]. It is a way to fulfill the need for transparency and accountability [13]. Open Data could be seen as a part of FAIR, because the goal of open data can be achieved by following the first three FAIR guidelines [13].

Moreover, Open Data and the FAIR principles provide an important foundation for reproducibility, as they enable researchers to share their data [5] and thereby promote transparency in research.

2.2 Reproducibility

Reproducibility is a cornerstone of scientific integrity [10]. Although its definition varies across fields, its core attribute is the ability of independent researchers to draw the same conclusions from an experiment by following the original documentation [9]. A distinction should be made from replication, which seeks to obtain the same results using new data and/or different computational methods [19]. However, others use those terms interchangeably [10].

In computational fields, reproducibility often focuses on sharing and annotating data and code, while in psychology and other empirical sciences, it may involve redoing experiments under similar conditions [10].

Strategies to enhance reproducibility include adopting Open Science practices, such as detailed documentation, open data, version control, and preregistration [12] [5] [22]. The Transparency and Openness Promotion (TOP) guidelines and tools like the Open Science Framework aim to address these challenges by promoting transparency and accountability in research [10].

The Open Science Handbook[5] provided clear instruction on how to incorporate reproducibility into research:

- Preregister important study design and analysis information to increase transparency and counter publication bias of negative results
- Track changes to your files, especially your analysis code, using version control like Git
- Share your used Data and Materials, like software and hardware
- Report your methods and results explicitly and transparently to allow reproduction

Improving reproducibility leads to increased rigor and quality of scientific outputs, and thus to greater trust in science [5].

Even with its recognized importance, reproducibility faces significant challenges. For example, a study of 133 papers in learning analytics found that none could be reproduced within a 15-minute time-frame, primarily due to missing libraries, undocumented randomness, or platform-specific dependencies [12]. Beyond technical issues, reporting practices play a crucial role in supporting reproducibility. The explicit reporting of limitations is a non-negotiable element, equally important as providing open access to data [15]. Likewise, researchers must explicitly describe their methodological approach and decision points to avoid constraining reproducibility and replicability [15] [16]. Clearer reporting of research choices, processes, and results can help reduce misinterpretation and avoid the mistaken reporting of findings [16]. Another challenge is the insufficient access to data [12] [15] [16]. Often, insufficient documentation makes it difficult to understand the data processing steps, the rationale behind analytical choices, or even to locate the necessary materials [12]. Despite ongoing efforts to encourage greater data sharing in learning analytics, only a few research groups release their datasets publicly [12] [16]. These persistent technical and reporting challenges highlight the need for greater transparency in methodological and analytical choices to advance reproducibility in the field [15] [16].

In General, this lack of transparency, combined with inconsistent implementation of open science and reproducibility principles, has significantly hindered reproducibility efforts, highlighting a growing concern in scientific research [10].

2.2.1 Reproducibility Crisis

The ongoing difficulty in reproducing research findings has led to what is now commonly referred to as the *Reproducibility Crisis* [10]. A 2016 poll conducted by Baker [3] and published in the journal Nature found that over half (52%) of surveyed scientists believed science was indeed facing a reproducibility crisis. Others have a more optimistic view on the situation. For example, Vazire [28] instead refers to it as a *credibility revolution*. Spellman [25] calls it *Revolution 2.0*, a time where research, with the help of technology, improves by allowing full descriptions of methods, making data sets and analysis code available, preregistration of studies, and fostering a culture of transparency and accountability in scientific practices. The early creation of the Open Science Framework has provided an existence proof that these things can easily be implemented [25]. Again, underlining the importance of transparent and open research.

Despite these advances, concerns about reproducibility remain widespread. A recent 2025 survey of 452 professors across India and the USA reported that approximately 80% of Indian researchers and over 90% of U.S. researchers were familiar with the reproducibility crisis [6]. However, nearly 20% of respondents believed their peers remained completely unaware of the issue [6]. The survey also identified key barriers to reproducibility, with the majority of engineering researchers in both countries citing the unavailability of raw data as the primary obstacle, followed closely by the lack of access to code [6]. Other prominent challenges included selective reporting and publication pressure [6]. When it came to reproduction attempts, only 15% of Indian researchers who tried to reproduce others' work reported affirmative results, compared to 33% in the USA [6]. A common reason for unsuccessful reproduction was the lack of adequate methodological information provided in published studies [6]. However, better community practices such as sharing code and maintaining detailed project pages on platforms like GitHub have made reproducibility easier over time [6]. Proper documentation, along with accessible data and code, is now recognized as critical to successful reproduction [6]. While reproducing others' work was significantly more challenging in the past, the situation has improved considerably in step with the open science movement [6]. Nevertheless, the adoption of open science principles remains inconsistent across research communities. For instance, Haim et al. [12] found that the Learning Analytics community still has substantial room for improvement in this area. Continued efforts are needed to incentivize data and code sharing, enhance methodological transparency, and more fully integrate open science practices into standard research workflows.

2.3 Natural Language Processing

Natural Language Processing (NLP) is a subfield of Artificial Intelligence (AI) that focuses on enabling machines to interpret, generate, and interact using human language [17]. Because of its ability to process and understand large volumes of text, NLP has enabled a broad range of practical applications [18]. Some of the most frequent applications are text classification, machine translation, information retrieval, and question answering , but NLP also encompasses a wide range of other tasks [18].

2.3.1 Large Language Model

A Large Language Model (LLM) is a type of AI system designed to understand and generate human language. Built upon deep learning architectures, particularly the Transformer [27], LLMs represent one of the most advanced developments in NLP [18]. They are trained on massive text corpora to learn linguistic patterns, grammar, facts, and reasoning abilities [18]. These models are capable of performing a wide range of NLP tasks, such as machine translation, text summarization, question answering, and sentiment analysis [18]. Some of the currently best-performing models are Grok-3-Preview-02-24, GPT-4.5-Preview, Gemini-2.0-Flash-Thinking-Exp-01-21, and DeepSeek-R1 [11].

LLMs operate within a defined context window, which limits how much text the model can consider at one time. The model's input, known as a prompt, guides its output. Prompt engineering involves crafting inputs to elicit desired behaviors or responses from the model [23].

The temperature parameter controls the randomness of the model's output. Lower values (e.g., 0) make responses more deterministic and focused, while higher values (e.g., 0.8) encourage diversity and creativity [20]. This allows users to fine-tune how conservative or imaginative the model's output should be, depending on the task at hand. However, it should be noted that setting the temperature to 0 does not guarantee a fully deterministic output [20]. In the context of reproducibility, the temperature should be set to 0 to make sure the output is as reproducible as possible.

When used together, these methods allow for controlled generation of outputs targeted at specific applications. Such capabilities are being leveraged in academic research workflows, where LLMs can support or automate tasks normally performed by human researchers, like summarizations or coding [14] [4].

2.3.2 Use-cases of LLM in research

Keya et al. [14] leveraged the use of LLMs for scientific abstract summarization in 2025. In their study, each abstract was condensed into a single sentence by an LLM and subsequently evaluated both automatically and by human reviewers. They compared multiple models across various prompting techniques and analyzed performance across several scientific domains, including computer science [14]. Their key findings highlight, first, that automated evaluation results aligned closely with human assessments, and second, that the choice of prompting technique plays a significant role in optimizing LLM performance, with different models benefiting from different approaches [14].

In another study from Bermejo et al. [4], the effectiveness of LLMs in extracting complex information from textual data was evaluated . In their work, both human coders and LLMs were tasked with performing increasingly complex information retrieval tasks using newspaper articles that required substantial contextual understanding [4]. Across all tasks, the LLMs consistently outperformed human participants, even when dealing with lengthy and challenging texts, indicating their superior performance [4]. These results highlight the significant advancements in NLP technology and demonstrate that sophisticated textual analyses can now be readily implemented by researchers, even without extensive prior expertise in the field [4].

Together, these studies illustrate the strong potential of LLMs for text extraction and analysis. They demonstrate that LLMs are capable of identifying and extracting relevant information from complex texts. This should make them well-suited for tasks such as analyzing research papers for reproducibility.

2.4 Gemma 3

Gemma 3 is the latest lightweight open language model developed by Google DeepMind [11]. One of its key features is the support for long context lengths of up to 128K tokens, enabling it to process multi-page documents or lengthy articles in a single pass [11]. The model incorporates advanced filtering techniques to reduce the risk of generating unwanted or unsafe content and to remove personal or sensitive information from its output [11].

Despite its relatively modest size, the instruction-tuned Gemma 3-27B-IT variant ranks among the top 10 models in the Chatbot Arena benchmark [7], outperforming significantly larger models such as DeepSeek-V3 and Qwen2.5-70B [11].

Designed for efficiency, the model runs on standard consumer-grade hardware, including phones, laptops, and high-end GPUs, while maintaining strong performance across a range of tasks [11]. It is also openly available: users can interact with it via an API (with free and unlimited access, provided token limits are respected) or run it locally using platforms like Hugging Face or Ollama.

In this thesis, Gemma 3 is used in the pipeline to automatically evaluate the reproducibility of research papers, selected for its strong instruction-following and long-context capabilities, as well as its open-access nature and freely available API, which make it both practical and accessible for academic use.

2.5 Education Technology and Learning Analytics

Education Technology is a field focused on developing and evaluating tools and processes to enhance learning and teaching. It operates in a cyclical manner: Researchers create new technologies, educators and learners provide feedback, and researchers refine their innovations based on these data [12]. A prominent subfield within Education Technology is Learning Analytics, which involves collecting and analyzing data from learners to improve educational outcomes [24]. It emerged as a distinct discipline with the establishment of the International Conference on Learning Analytics and Knowledge (LAK) in 2011 [24]. Over the years the field has grown and diversified and was recently redefined as follows:

> *Learning analytics is the collection, analysis, interpretation and communication of data about learners and their learning that provides theoretically relevant and actionable insights to enhance learning and teaching. (SoLAR2025)*

Learning Analytics is a human-centered, multidisciplinary field focused on the intersection of data and learning [24]. The LA community conducts theory-driven investigations into learning processes that are relevant to various stakeholders, such as students, teachers, learning designers and advisors [24]. It informs feedback and offers actionable insights. The goal is to improve learning, learners' well being and the quality of education [24].

Rooted in practical application, LA takes a holistic approach to data: encompassing data collection, analysis, communication, and feedback, all to provide insights back to stakeholders [24]. These insights inform actions such as implementing educational interventions. The field is guided by responsible, sustainable, and ethical data use [24]. By leveraging evidence-based and contextually-aware data from educational technologies, strategic and operational decisions can be made to support learners, teachers, and other educational stakeholders [24]. Alongside quantitative methods—such as statistical approaches, machine learning, and other AI techniques—qualitative methods, mixed approaches, and insights from the learning sciences are also employed to enhance learning [24].

Because research in Learning Analytics builds upon previous findings, it is crucial to trust the reliability and validity of existing work before using it as a foundation for new insights. This makes reproducibility and adherence to open science practices essential. For this reason, I propose the development of a reproducibility checking pipeline, designed to help the Learning Analytics community assess the reproducibility of published studies and provide support to researchers in implementing reproducible practices.

Chapter 3

Implementation

This chapter outlines the approach used to design and evaluate the reproducibility checking pipeline. The goal of the pipeline is to automatically assess to what extent a research paper satisfies a predefined checklist of reproducibility criteria. To achieve this, I developed an open software prototype that analyzes academic papers. PDFs are processed in Python, with relevant sections extracted and evaluated using the Gemma 3 language model against a reproducibility checklist.

Figure 3.1 illustrates the overall approach. The process begins with the creation and iterative revision of a reproducibility checklist. Next, a prototype implementation is developed and evaluated in a study with human participants, during which the checklist is also assessed to ensure it captures all key elements needed for reproducibility. Building on these results, the prototype is then applied to analyze the current reproducibility state of LAK'25. Finally, the outcomes are presented and compared with earlier findings from the Reproducibility Review of LAK'21/22 [12].

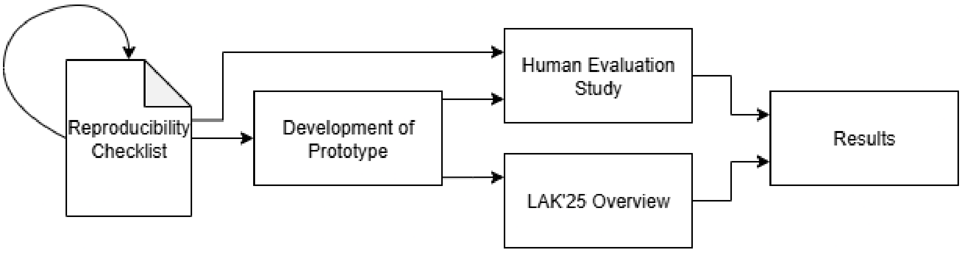


Figure 3.1: Overview of the Approach used for this Thesis

3.1 Reproducibility Checklist

The core of the pipeline relies on a reproducibility checklist designed to capture key elements necessary for a research paper to be considered reproducible. The checklist includes categories such as detailed methodology description, availability of data, access to code, clarity of results, and preregistration. These categories were selected based on open science and reproducibility criteria mentioned earlier in Chapter 2 and reflect essential components needed for reproducible research. The checklist was refined through multiple iterations by the help of a subject matter expert to ensure completeness and clarity throughout this thesis.

The checklist is briefly summarized below in Table 3.1 and can be found in Appendix A.

Category	**Summary of Key Criteria**
Open Methodology & Documentation	Clear explanation of methodology and a step-by-step description of the study or experiment.
Data Accessibility & Transparency	Datasets openly available, well-documented, and collected through transparent methods.
Code & Software Availability	Code is shared in a public repository and includes scripts for data preparation and analysis.
Type of Analysis	Research and analytical methods are described clearly, including models, assumptions, and coding practices.
Results & Interpretation	Transparent reporting of outcomes and discussion of limitations and potential biases.
Preregistration	Checks whether the study was preregistered.

Table 3.1: Summary of the reproducibility checklist categories.

3.1.1 Open Methodology & Documentation

This criterion addresses the transparency and detailed description of the research process. Clear and comprehensive documentation of the methodology is essential, as it enables others to reproduce the study accurately. Without such documentation, reproduction becomes challenging or impossible. For instance, if a paper does not provide a step-by-step description of the methodology, important steps may be omitted, leading to ambiguity and making reproduction difficult.

3.1.2 Data Accessibility & Transparency

This criterion focuses on the openness, documentation, and collection methods of the data used. Reproducibility requires applying the same methods to identical data, making data accessibility and understanding critical. To enhance transparency, the data collection process should be explicitly described. Without access to the original data, reproducibility is not possible.

3.1.3 Code & Software Availability

To reproduce a study, access to the code and software used is necessary. These should be shared through a publicly accessible repository, such as GitHub, and include all scripts for tasks like data preparation and preprocessing to ensure consistency across multiple runs. Without such access, even small implementation details, such as data cleaning steps, parameter settings, or library versions, can remain unclear, making accurate reproduction difficult or impossible.

3.1.4 Type of Analysis

The researchers should provide clear descriptions of the analysis type, whether quantitative or qualitative. For quantitative methods, all statistical tests, methods, and assumptions must be explicitly stated, and if effect sizes, confidence intervals, or p-values are used, they should be reported. This allows for comparison and validation of results upon reproduction. For qualitative methods, the subjective context and interpretations of participants and data should be detailed [8]. Additionally, data coding and analysis processes should be shared to enhance transparency and reproducibility in qualitative research [8].

3.1.5 Results & Interpretation

Results must be thoroughly documented to enable comparison and validation after reproduction. Since reproducibility requires comparing newly obtained results with the originally reported ones, complete and transparent reporting of results is essential. To further increase transparency, limitations and potential biases should also be discussed, as this minimizes subjective interpretations and strengthens the reliability of the findings.

3.1.6 Preregistration

While preregistration may seem unnecessary if methods, data, code, and results are well-documented, it significantly enhances transparency and mitigates publication bias, particularly for negative results [5]. As highlighted in the Open Science Handbook [5], preregistration helps address the reproducibility crisis and promotes open science practices. Therefore, studies should be preregistered, with a link provided to the preregistration (e.g., on the Open Science Framework).

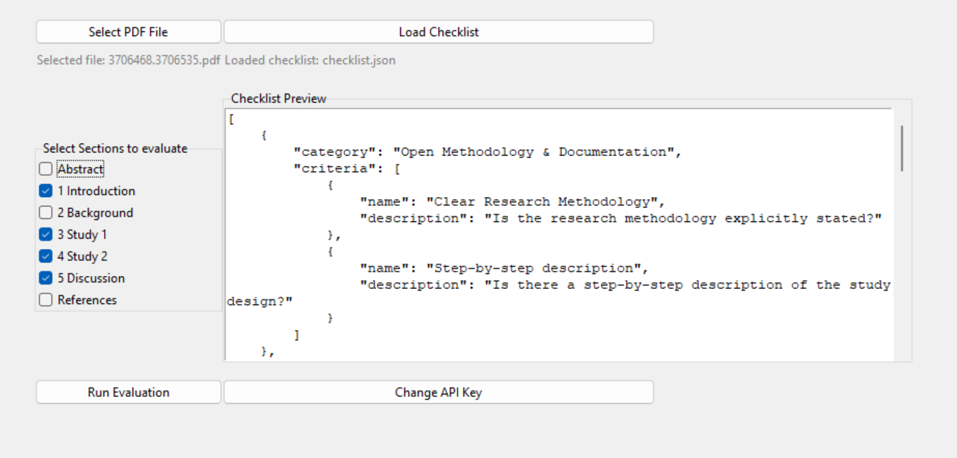
3.2 Reproducibility Checking Prototype

All code for this thesis was written in Python 3.13 and is available in the following GitHub repository: `https://github.com/domkka/bachelorthesis/tree/main/pythonprototype`

To install all required packages, the following command should be executed:

pip install -r requirements.txt

The **tkinter** package was used to implement the user interface, which can be seen in Figure 3.2. There are four buttons with the following functions: **Select PDF File**; **Load Checklist**; **Change API Key**; **Run Evaluation**.



Selected file: 3706468.3706535.pdf Loaded checklist: checklist.json

Select Sections to evaluate

☐ Abstract
☑ 1 Introduction
☐ 2 Background
☑ 3 Study 1
☑ 4 Study 2
☑ 5 Discussion
☐ References

Checklist Preview

```
[
    {
        "category": "Open Methodology & Documentation",
        "criteria": [
            {
                "name": "Clear Research Methodology",
                "description": "Is the research methodology explicitly stated?"
            },
            {
                "name": "Step-by-step description",
                "description": "Is there a step-by-step description of the study
design?"
            }
        ]
    },
```

Figure 3.2: Reproducibility Checking Pipeline GUI

Figure 3.3 illustrates the workflow of the pipeline, showing which functions are called and how they relate to each other:

When the **Select PDF File** button is pressed, the function `load_pdf()` is called. A file dialog window opens, allowing the user to choose a research paper in PDF format. The selected document is then processed using the **pypdf** package. Text extraction and sectioning are performed by the function `extract_sections_using_bookmarks()`, which searches the complete text for headings corresponding to PDF bookmarks and splits the document accordingly, storing each section separately. After loading the paper, a new interface frame appears, listing all detected sections. Users can choose specific sections for evaluation by selecting the corresponding checkboxes. Prior to evaluation, the text is filtered to include only the selected sections, thereby reducing the token length and ensuring that the language model focuses on the most relevant content. For example, uninformative parts such as the *References* section can be excluded if not selected, as they do not contribute meaningfully to checklist-based reproducibility assessment. By clicking the **Load Checklist** button, the `load_checklist()` function is triggered. This function allows the user to select a JSON file, ideally the `checklist.json`; however, the checklist can also be modified as long as the same structure is maintained. Providing a correctly formatted checklist is essential to ensure that the evaluation pipeline functions as intended and produces valid output. When the checklist is loaded, it is also previewed in a separate frame within the interface. To make requests to the Google Gemini API, an API key is required. A key can be generated at: `https://aistudio.google.com/apikey`. To integrate the key with the pipeline, it must either be saved as an environment variable named `GEMINI_API_KEY`, or entered manually into the corresponding field in the user interface after clicking the **Change API Key** Button. After loading the checklist and selecting the desired sections from the PDF, the evaluation is performed by clicking the **Start Evaluation** button, which triggers the `run_evaluation()` function. In this step, the selected sections and the checklist are combined into a prompt, which is then sent to the Gemma 3 model via an API request in the `generate()` function . The **google-genai** package is used to handle these API calls. Upon receiving a successful response, the output must be parsed back into valid JSON with the help of the `extract_json_from_response()` function, since it includes backticks and formatting prefixes despite explicit instructions not to. Finally, the completed checklist is saved in JSON format and displayed in the preview frame. With the help of the **auto-py-to-exe** tool, the python code was compiled to an executable, making it easily shared to other users.

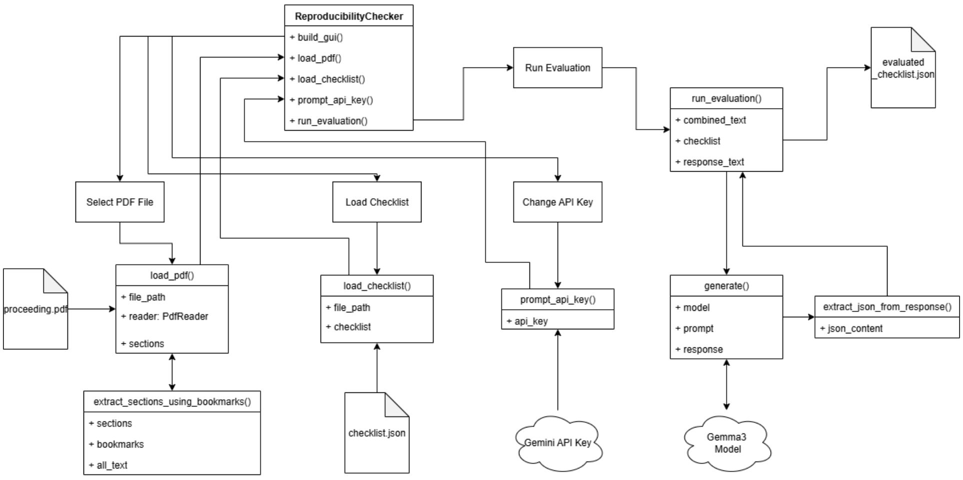


Figure 3.3: Detailed view of the Pipeline's Workflow

3.3 Checklist Verification with Language Models

The text extracted from each paper was analyzed using natural language processing techniques to automatically identify whether the checklist criteria were met or not. For this task, a large language model (LLM), the open-source Gemma 3 model, was used via its free API calls. For Prompting, a zero-shot-approach was taken, which includes the evaluation task, the sliced research paper and the reproducibility checklist. Also it was instructed to only fill out the checklist and return it as a JSON String. After refining the prompt to comply with the instructions, the final version is presented below:

```
Evaluate the following document with respect to the checklist criteria below:

Document:
"""{pdf_text}"""

Checklist:
{checklist}

For each checklist item, provide:
- ‘criterion‘: the name of the checklist item
- ‘status‘: one of "Met", "Not Met"
- ‘justification‘: a short explanation of where or why the criterion is (not) met
(e.g., section title, paragraph context, or quote)

Output format:
Return only valid JSON, structured like this:
[
    {
        "category": "Open Methodology & Documentation",
        "results": [
            {
                "criterion": "...",
                "status": "Met" | "Not Met",
                "justification": "..."
            }
        ]
    },
    ...
]
Do not include any explanation or commentary outside the JSON.
```

3.3.1 Possible Problems

Despite using a deterministic temperature setting of 0 for all API calls, there could be some reproducibility issues when trying to evaluate the same paper again. In some rare cases, the model gave papers neither the status "Met" nor "Not Met", but rather "Partially Met" or "N/A" even though it was not prompted to do so. While the language model provides short explanations for each classification, the underlying decision-making process remains largely opaque due to the inherent nature of LLMs. However, to increase transparency, the model also returns the specific sections or text snippets from which the relevant information was extracted, or provides links that support the assessment. This helps to ground each evaluation in the original context and provides traceability for further manual verification.

3.4 Human Evaluation

The Pipeline is evaluated through a user study. Each participant is assigned two randomly selected papers from the LAK'25 Conference. Participants include four experienced researchers from the Learning Analytics academic community as well as three less experienced researchers currently in their last semester in Computer Science.

Each paper is evaluated twice: first manually using the provided Reproducibility Checklist, and then automatically using the Prototype Pipeline. After both evaluations, participants complete a survey regarding the usefulness and completeness of the Checklist as well as the accuracy and usability of the Pipeline. This process enables a thorough assessment of the Checklist's coverage and the effectiveness of the Pipeline, while also helping to identify potential areas for improvement.

By directly comparing the manually completed Checklists with those automatically generated by the Pipeline, we can evaluate the accuracy of the language model.

The survey includes Likert scale questions and open-ended questions to gather quantitative and qualitative feedback. The study process and the survey can be found in Appendix B and C.

3.5 Scoring for Proceedings Overview

The LLM's output for each paper is parsed as a JSON object making it easily readable and usable for further processing steps. Each paper is assessed according to the checklist and each category is rated as either "Met" or "Not Met". To achieve an overall status of "reproducible," a paper must fully meet all criteria.

The rationale for this strict scoring system is that the absence of a single component could compromise the ability of other researchers to reproduce a study's findings. Thus, one missing criterion is sufficient for a paper to be classified as not reproducible. This scoring scheme enforces a high standard and ensures that only papers meeting all fundamental reproducibility conditions are acknowledged as such.

Preregistration is treated as a bonus category and does not influence the overall reproducibility rating. While preregistration is not strictly necessary for a study to be reproducible, it plays a critical role in addressing publication bias and enhancing the credibility of research by making a prior hypotheses and methods transparent.

The scoring was performed using a separate Python script, `jsonscorer.py`, which processes the generated JSON files and applies the defined evaluation rules. Although not part of the main pipeline, this script is an essential post-processing step in the reproducibility assessment for both the Study and the overview of the reproducibility state of LAK'25.

Chapter 4

Results & Interpretation

This chapter presents the results of the study conducted to evaluate the reproducibility checking pipeline. First, the outcome of the human evaluation is described and compared to the pipelines. Subsequently, the findings are interpreted and discussed with respect to the pipeline's effectiveness, while also highlighting potential areas for improvement. Finally, the results of the evaluation of all research articles from the 2025 Learning Analytics & Knowledge Conference are presented to provide an overview of the current state of reproducibility in the field, as well as to identify potential improvements and insights for future work.

4.1 Study results

The study included a total of seven participants, four experienced researchers from the Learning Analytics academic community and three less experienced researchers, specifically students. Consequently, 14 papers were evaluated, where each one was assessed twice: once manually with the Reproducibility Checklist and once using the pipeline prototype. The evaluation results are presented and compared in the following figures, where each bar represents the manually or prototype evaluated papers. Finally, the Likert-scale responses from the survey, as well as the answers to the open-ended question, are also presented.

4.1.1 Reproducibility Scores

Figure 4.1 presents the distribution of reproducibility scores across both evaluation methods. One point is awarded for each applicable criterion on the checklist, with a maximum score of 5 points. In the manual evaluations, scores ranged from 1 to 5: one paper received a score of 1, one a 2, six papers were rated 3, three received a 4, and three were rated 5. In contrast, the pipeline evaluation produced scores ranging only from 3 to 5, with eight papers receiving a 3, three a 4, and three a 5.

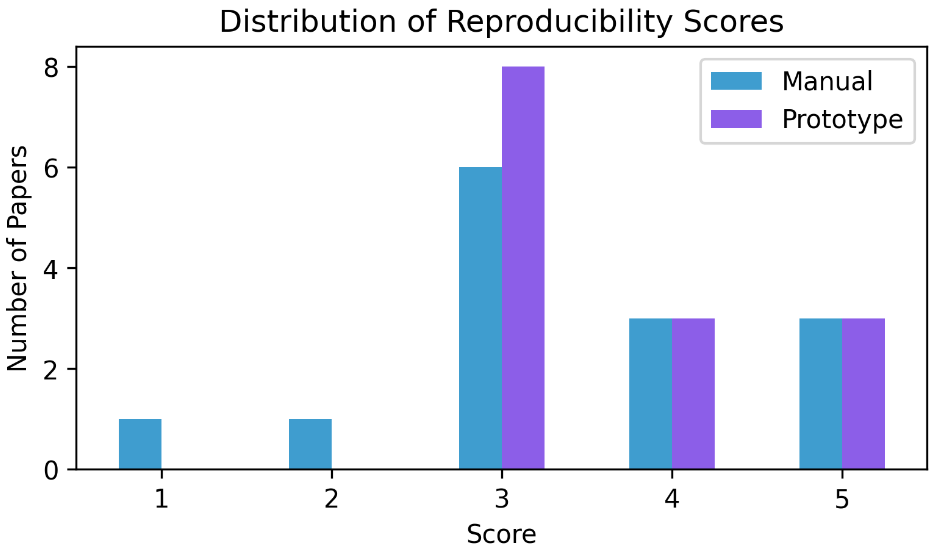


Figure 4.1: Distribution of Reproducibility Scores Manual vs Prototype Evaluation

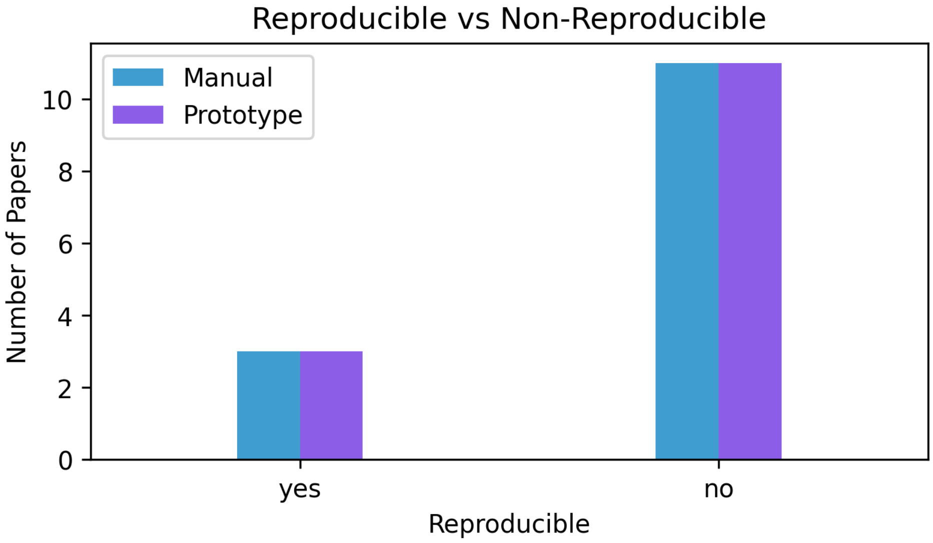


Figure 4.2: Number of papers deemed Reproducible or Not

Based on these scores, Figure 4.2 shows the absolute number of papers classified as reproducible or not. In this context, only papers that received the maximum score of 5 were considered reproducible. According to this criterion, three out of the 14 papers were deemed reproducible in both evaluations.

4.1.2 Reproducibility Criteria

To provide a more detailed view, the next figures break down which specific reproducibility criteria were met or not.

Figure 4.3 shows the number of papers that met the Open Methodology & Documentation criterion from the checklist. In the manual evaluation, only one paper did not meet this criterion. This was justified by the observation that the methodological steps were only briefly described and lacked a detailed explanation. In contrast, the prototype deemed the same paper compliant.

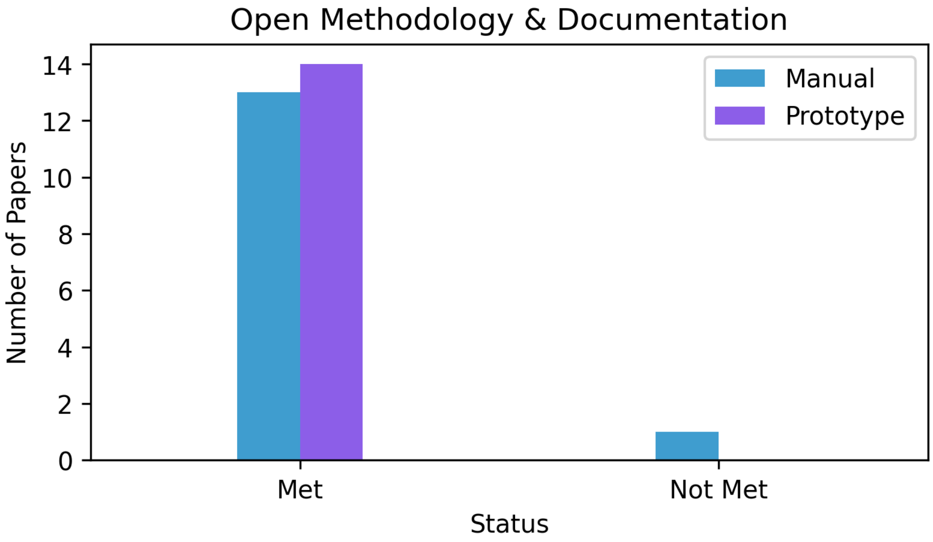


Figure 4.3: Number of papers meeting the Open Methodology & Documentation criterion

As shown in Figure 4.4, the results for the Data Accessibility & Transparency criterion reveal a larger discrepancy between the evaluation methods. In the manual evaluation, 7 papers were deemed to share data, whereas the prototype identified only 5 as containing shared data. In one instance, the prototype even indicated where the data could be found but still did not assign a “Met” status. In another case, the data was presented within a table but was neither externally published nor linked for the prototype to find. For the Code & Software Availability criterion, Figure 4.5 shows that three papers met the criterion in the manual evaluation. In contrast, four papers were classified as meeting the criterion in the pipeline-based evaluation. For one paper flagged by the pipeline as meeting the criterion, a GitHub link was provided; however, upon manual inspection, no code was found and only a PowerPoint slide deck was available.

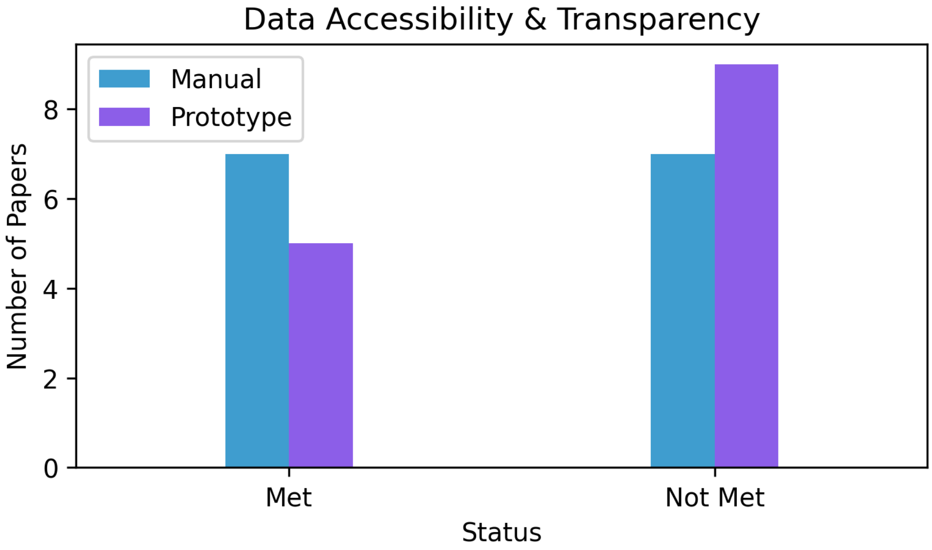


Figure 4.4: Number of papers meeting the Data Accessibility & Transparency criterion

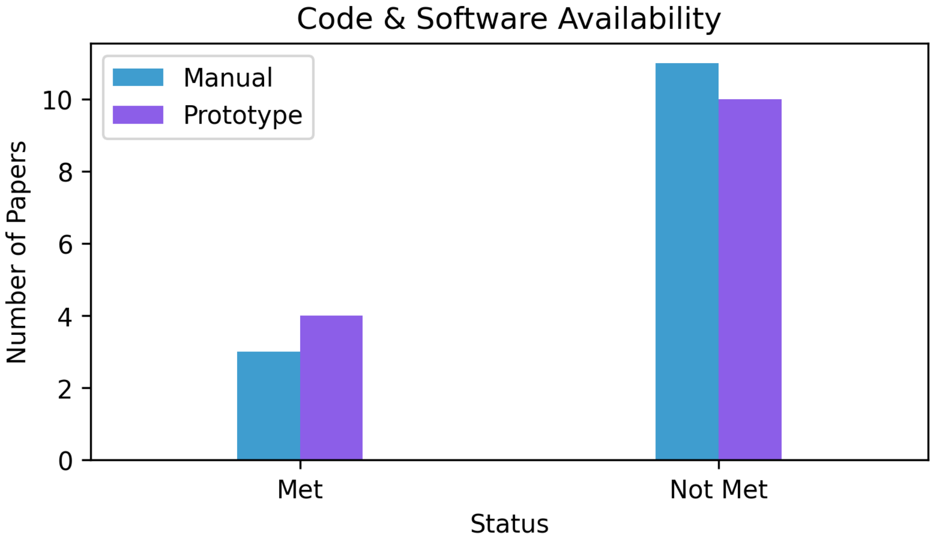


Figure 4.5: Number of papers meeting the Code & Software Availability criterion

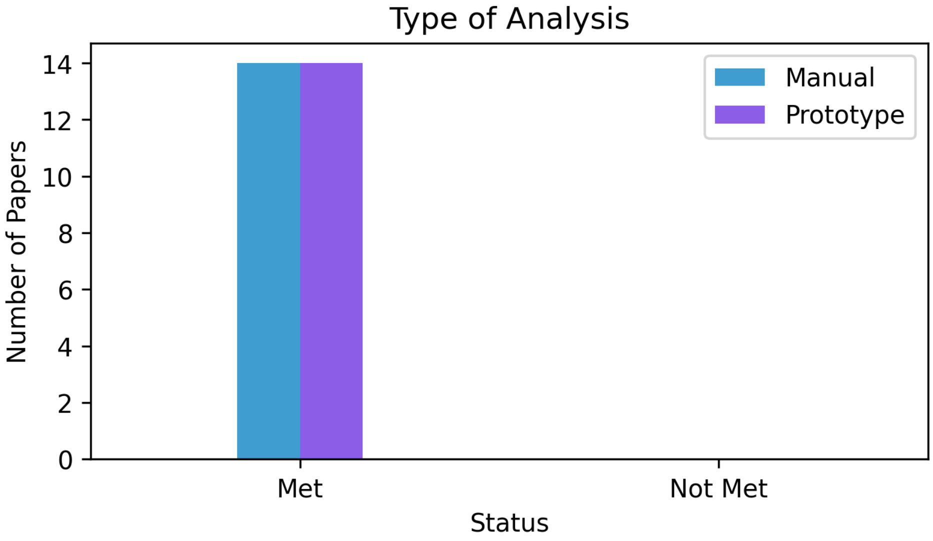


Figure 4.6: Number of papers meeting the Type of Analysis criterion

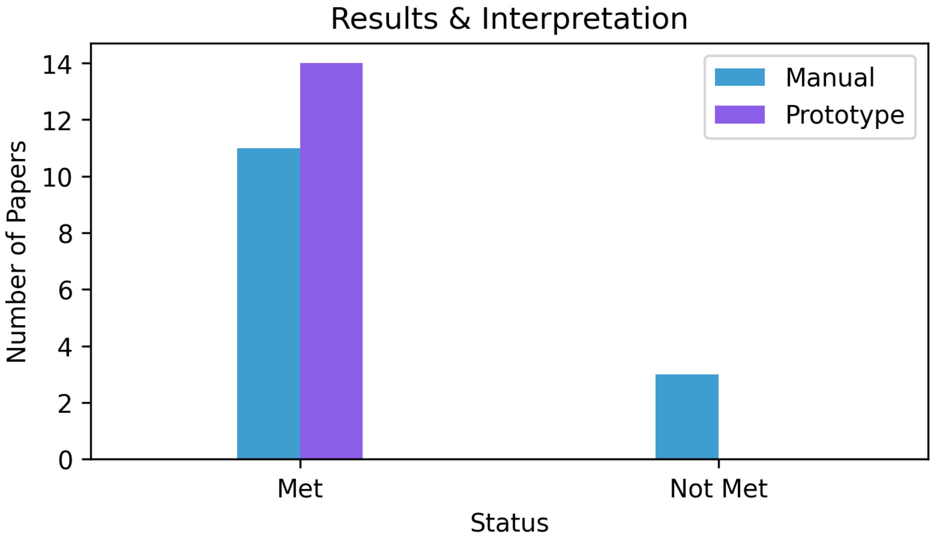


Figure 4.7: Number of papers meeting the Results & Interpretation criterion

The number of papers that meet the Type of Analysis criterion is shown in Figure 4.6. Here, the 14 papers met this criterion in both evaluation methods. Figure 4.7 shows that, in the manual evaluation, three out of 14 papers did not meet the Results & Interpretation criterion. This was again justified by the fact that the interpretation sections in those papers were not deeply enough discussed. In contrast, the prototype did not identify any issues, and consequently, all 14 papers were marked as meeting the criterion. Lastly, the Preregistration criterion was evaluated. As shown in Figure 4.8, only one paper included a link to a preregistration, and this was identified by both evaluation methods.

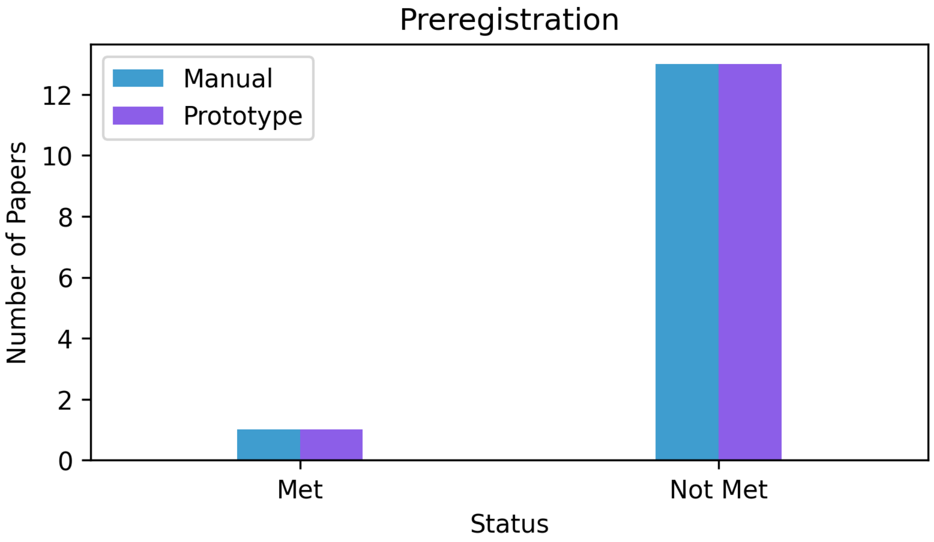


Figure 4.8: Number of papers meeting the Preregistration criterion

4.1.3 Survey Results

The survey (Appendix C) for the human evaluators consisted of four questions related to the Reproducibility Checklist, five questions focused on the pipeline prototype, and three open-ended questions for additional feedback. Figure 4.9 shows the average Likert scores for each question on a 5-point scale. Overall, the responses indicate a positive perception of both the checklist and the pipeline prototype. For instance, Question 2 (“The checklist captures key elements of reproducibility”) and Question 4 (“The checklist helped identify reproducibility aspects”) both received an average score of 4.71. Similarly, Question 6 (“The prototype has a clear use case”) was also rated highly. Questions related to the pipeline’s usability and usefulness received consistently strong ratings as well. The lowest-rated item was Question 9 (“I trust the pipeline’s output when assessing reproducibility”), with an average score of 3.8, reflecting that the pipeline’s outputs did not always align with the manual evaluations. The open-ended responses highlighted that the prototype improved the workflow by offering a

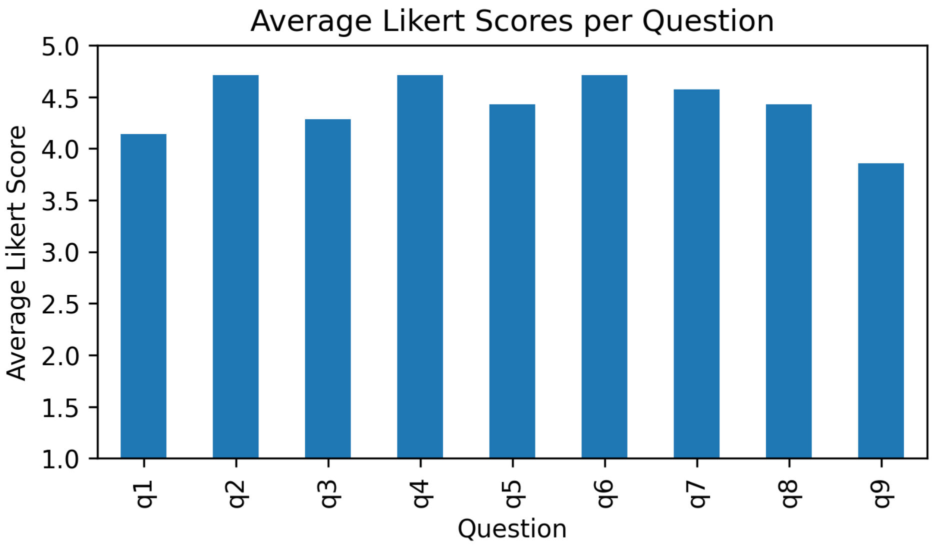


Figure 4.9: Average Likert Scores per Question

fast, automated assessment process. Participants noted that it saved time by reducing the need to read entire papers in detail and supported the creation of a mental framework when assessing research.

4.2 Pipeline Results for LAK'25

To provide an overview of the reproducibility state at LAK'25, all available research articles were evaluated using the reproducibility checking prototype. The proceedings are open access and can be found here [1]. In total, 70 research articles were evaluated. The following figures present the evaluation results.

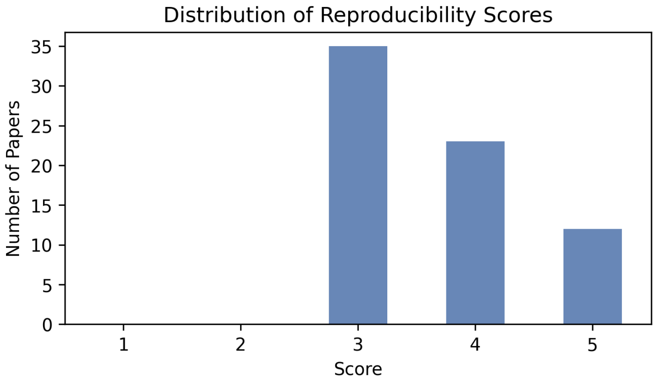


Figure 4.10: Distribution of Reproducibility Scores

Figure 4.10 shows the distribution of reproducibility scores across the evaluated proceedings. Of the 70 papers, 35 received a score of 3, 23 received a score of 4, and the remaining 12 received the maximum score of 5. Based on this scoring, 12 papers are considered reproducible, as illustrated in Figure 4.11.

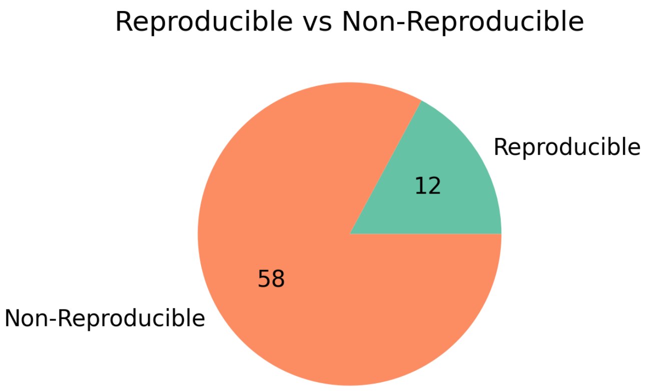


Figure 4.11: Reproducible vs Non-Reproducible

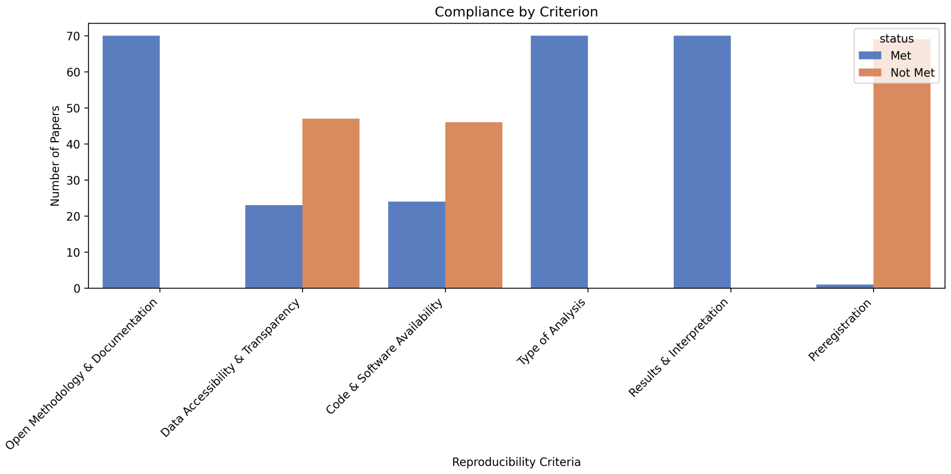


Figure 4.12: Compliance by Criterion

Figure 4.12 shows the compliance levels by criterion. All 70 papers received a 'Met' status for the criteria Open Methodology & Documentation, Type of Analysis, and Results & Interpretation. This may indicate that these criteria were indeed fulfilled in every case, or, as the study suggests, that the language model's assessment may lack sufficient quality. For the criterion Data Accessibility & Transparency, 23 papers provided open data. It should be noted that, of the 47 articles that did not include open data, 17 were evaluated as having a justified reason for this such as privacy concerns when publishing datasets. Similarly, 24 proceedings met the Code & Software Availability criterion. However, for those that did not share their code, no justification was provided. Lastly, only one paper was found to be preregistered.

4.2.1 Comparison to Open Science Principle and Reproducibility Review of LAK'21/22

When comparing the results to the Open Science: Principle and Reproducibility Review of LAK'21/22 [12], similar patterns emerge two years later, as visualized in Figure 4.13. All papers met the Open Methodology criterion, which aligns with expectations given the structured submission requirements for LAK papers.

In terms of Open Data, there appears to be a positive development. Whereas approximately 25% of papers in LAK'21/22 shared open data, this share has now increased to around one-third. This upward trend may be linked to the updated LAK guidelines, under which all proceedings are now Open Access, unlike earlier classifications that included Available, Open Access, and Public Access. Of the 70 evaluated papers, 17 cited valid reasons for not sharing data, such as privacy concerns. Assuming those papers make their data available upon request for reproduction, the proportion of papers sharing their data approaches 50%. Nevertheless, alternative approaches to data sharing could be considered, like censoring sensitive information while still making the remaining data accessible.

Similarly to Open Data, the situation regarding Open Materials and Code also appears to have improved. While only approximately 13% of papers openly shared their code in 2021 and 2022, this number has increased to around one-third in the current evaluation.

Regarding preregistration, only one paper was found to be preregistered, same as it was in the findings from LAK'21/22. This indicates that preregistration remains a low priority among researchers in this field. However, preregistering a study for an annual conference can be challenging due to time constraints.

In this review, 17% of papers were found to fully comply with all specified reproducibility criteria. By comparison, only 5% of papers in 2021 and 2022 fully met the broader open science principles defined by Haim et al. [12], which included open methodology, open data, and open materials, along with additional checks such as README files and licenses. Thus, the two results are not fully comparable, since reproducibility is a subset of open science and therefore somewhat easier to fulfill.

Their review [12] also included attempts to actually reproduce the research within a 15-minute time frame, which they considered reasonable, assuming that only a few setups, preprocessings, and analyses needed to be run. All attempts were unsuccessful, but it was estimated that 2% of papers containing both raw datasets and source code were likely reproducible given sufficient time and configuration. Although this thesis did not attempt to reproduce any papers, it is still likely that at least some papers complying with all criteria are indeed reproducible. But this also highlights an important distinction: even if a paper is evaluated as reproducible based on documentation and transparency criteria, it may not be practically reproducible in a rather limited time frame real-world attempt.

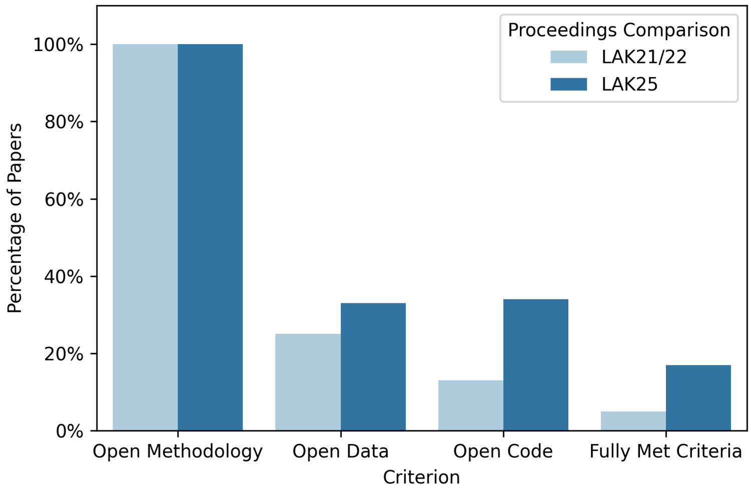


Figure 4.13: Comparison of LAK21/22 to LAK25

Chapter 5

Discussion and Limitations

The results of this study highlight both the strengths and limitations of the automated reproducibility checking pipeline. One of the key limitations lies in the pipeline's differentiation of superficial and detailed content. For example, in cases where methodological or interpretative descriptions were relatively vague or lacking in depth, the pipeline always marked these criteria as "Met," while human evaluators did not. This indicates that the pipeline may currently lack the sensitivity to assess qualitative depth in academic writing. Moreover, the sample size for this study may be somewhat limited, particularly considering that three of the seven participants were less experienced researchers. This could have affected their ability to accurately assess qualitative depth in academic writing, potentially leading to an overestimation of the pipeline's performance.

Additionally, there were instances where the pipeline failed to detect data that had been shared, possibly due to format, placement, or phrasing within the paper. This limitation suggests that the pipeline may require further optimization to accurately identify and interpret links or references to supplementary material. It is also worth noting that the current implementation uses the Gemma 3 model, which is a less costly but still capable large language model. Replacing it with an even more powerful model could improve performance by enabling larger context windows and more in-depth textual analysis, potentially enhancing the accuracy of the evaluation.

When examining the reproducibility checklist results more closely, three criteria from it were consistently marked as "Met" by the pipeline across all papers. On one hand, this could indicate that the papers were genuinely compliant with these aspects. On the other hand, it may suggest that the criteria of the reproducibility checklist and the way they are phrased, lack sufficient depth to allow meaningful differentiation from the LLM. This raises the possibility that these criteria could be revised again or divided into more granular sub-questions. Doing so could help the language model better distinguish between superficial and thorough chapters.

Currently the pipeline has some compatibility issues regarding its execution on different operating systems. Since it was developed in Python on a Windows operating system and compiled into an executable using the **auto-py-to-exe** tool, it cannot be executed on non-Windows systems. This restricts cross-platform usability. Furthermore, the prototype currently supports only structured PDF files in order to reduce the input context size. This limits its ability to process unstructured documents, potentially excluding a subset of papers from evaluation. Especially for papers that do not follow the same structure as the LAK proceedings, splitting chapters can fail due to conflicts. For example, when trying to evaluate this thesis with the pipeline, it would not work because the bookmarks are already defined in the contents section. Therefore, an alternative approach is needed to extract the chapters. One method was tested and can be found in the GitHub repository under `/bachelorthesis/pythonprototype/altchecker`, where chapters are extracted using page numbers instead of regex searches.

Due to rate limitations imposed by the Gemini API, only a limited number of papers can be processed per minute, which can significantly increase evaluation time when analyzing multiple papers sequentially. In terms of output format, one participant noted that the current JSON structure may hinder readability. This suggests that converting the output into a more user-friendly format, such as a structured text report or table, could improve accessibility.

Despite these issues, the pipeline proved highly valuable in creating a structured overview of each paper. This capability significantly accelerates the evaluation process, especially when dealing with a large number of publications. In most cases, the pipeline's assessments were entirely accurate, providing a strong foundation for reproducibility screening. While the pipeline is not yet a full replacement for manual review, it demonstrates considerable potential as a time-saving support tool. What requires several hours of manual analysis can now be performed within minutes, making it a useful aid in large-scale reproducibility evaluations.

The overall reproducibility state of the Learning Analytics & Knowledge Conference appears to have improved. Although this study did not attempt to directly reproduce the research findings, improvements were observed in adherence to open science and reproducibility principles. Particularly, more code and data were shared compared to previous years, indicating progress in transparency. However, a persistent barrier remains: the use of personal or sensitive data, which often cannot be made publicly available.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Trust in research is foundational to scientific progress, and one of the most effective ways to build this trust is by ensuring that research is reproducible. However, the academic community continues to face a reproducibility crisis, where many published studies cannot be reliably reproduced. A key strategy to address this challenge lies in the adoption and enforcement of open science principles.

To contribute to this effort, this thesis introduced an automated reproducibility checking pipeline tailored to the Learning Analytics research community. The pipeline evaluates key aspects of reproducibility by analyzing published papers using a Large Language Model. It was applied to the latest LAK proceedings to assess the current state of reproducibility in the field and revealed an improvement in open science practices compared to prior years, particularly in the sharing of code and data. Nevertheless, persistent challenges remain, such as restrictions on sensitive datasets and the limited uptake of preregistration.

The study also identified key limitations of the pipeline: reduced sensitivity to qualitative depth in text, occasional failures in detecting shared materials, and technical constraints such as operating system compatibility, which ironically restricts its reproducibility. Despite this, it proved to be a useful tool for generating quick and informative overviews of research papers, reducing the time for evaluation. With further refinement and more powerful models, it has the potential to support researchers in conducting even faster and more consistent reproducibility assessments at scale.

6.2 Future Work

Future research could explore whether using more powerful Large Language Models would enhance the accuracy and nuance of evaluations, particularly for aspects such as methodology and interpretation. Alternatively, revising and expanding the current checklist into more granular items may enhance the depth and reliability of the pipeline's assessments. Additionally, to further validate the effectiveness of the pipeline, it would be valuable to attempt reproducing a selection of high-scoring papers. This could help determine whether the pipeline's output truly reflects the actual reproducibility of the research.

Appendix A

Reproducibility Checklist

Below the full Reproducibility Checklist can be found

Reproducibility Checklist DOI:		Met
Open Methodology & Documentation		
Clear Research Methodology	Is the research methodology explicitly stated?	□
Step-by-step description	Is there a step-by-step description of the study design?	□
Data Accessibility & Transparency		
Open Data	Are the raw or processed datasets publicly available or has it been mentioned where the data can be found?	□
	If data cannot be shared, is there a clear justification (e.g., privacy concerns)?	□
Data Documentation	Is there a data dictionary or codebook explaining variables, formats, and preprocessing steps?	□
Data Collection Methods	Are data collection methods fully described?	□
Code & Software Availability		
Open Source Code	Is the analysis code (Python, R, etc.) shared in an open repository (GitHub, GitLab) or somewhere else publicly available?	□
	If code cannot be shared, is there a clear justification?	□

Code for Data preparation	Is code for data preparation (e.g. pre-processing) shared/mentioned?	□
Type of Analysis		
Quantitative Research Methods	Are statistical tests, models, and assumptions clearly described?	□
	Are effect sizes, confidence intervals, and p-values reported?	□
Qualitative Research Methods	Is subjective context and interpretation given?	□
	Is data coding and analysis clearly described and shared?	□
Results & Interpretation		
Clearly presented Results	Have the results been clearly documented?	□
Limitations and potential biases	Are limitations and potential biases discussed?	□
Preregistration		
Preregistration	Does the Paper contain a link to the preregistration (e.g the Open Science Foundation)?	□

Appendix B

Study process

Below the full Study process can be found

Study Process for my Bachelorthesis on
“An Automatic Reproducibility Checking Pipeline for the Learning Analytics Academic Community”

You are given two randomly selected proceedings from the Learning Analytics & Knowledge Conference 2025, a Checklist (“Reproducibility Checklist.pdf”) and a Prototype (“reproducibilitychecker.exe”).

For each of the two proceedings fill out the Checklist:

- Write DOI at the top.
- Mark question as Met if the requirement is fulfilled.
- give a brief justification where in the paper the information is found (e.g, section, supplementary link, etc.)

After doing this for both proceedings, use the prototype to automatically evaluate the proceedings.

The prototype works as follows:

- Launch “reproducibilitychecker.exe” (Note: It might be flagged as an unrecognized app - click “More Info” -> “Run anyway”)
- Click “Select PDF File” and choose the proceeding
- Select the sections most likely to contain relevant information (Note: if everything is selected it might exceed the Token limit, e.g References should not be selected)
- Click “Load Checklist” and select the “checklist.json”
- Click “Change API Key” and copy-and-paste the API-Key found in “super-confidential-secret.txt“
- Click “Run Evaluation”

The automatically evaluated checklist can then be found in the preview window or in the directory: generatedjson/{doi}.json

Once you have evaluated both papers, please complete the small survey (Survey.pdf) and send me the filled checklists and survey to domenik.kern@stud.uni-hannover.de

Appendix C

Survey

Below the full Survey can be found

SURVEY

Thank you for participating in the study for my Bachelorthesis "An Automatic Reproducibility Checking Pipeline for the Learning Analytics Academic Community" . Your feedback is important as I continuously strive to improve my work. Please take a few minutes to complete this Survey.

PERSONAL INFORMATION:

Name:

Email Address:

Note: The information collected will be used solely for the purpose of this survey and will be kept confidential.

CHECKLIST EVALUATION:

Please rate the following aspects of the checklist on a scale of 1 to 5, where 1 stands for 'Strongly Disagree' and 5 stands for 'Strongly Agree'.

	1	**2**	**3**	**4**	**5**
Q1: The checklist consists of clear defined questions .	□	□	□	□	□
Q2: The checklist captures key elements of reproducibility.	□	□	□	□	□
Q3: The checklist is scalable to allow for more detailed assessment	□	□	□	□	□
Q4: The checklist helped identify reproducibility aspects.	□	□	□	□	□

PROTOTYPE EVALUATION:

Please rate the following aspects of the prototype on a scale of 1 to 5, where 1 stands for 'Strongly Disagree' and 5 stands for 'Strongly Agree'.

	1	**2**	**3**	**4**	**5**
Q5: The prototype is easy to use.	□	□	□	□	□
Q6: The prototype has a clear use-case.	□	□	□	□	□
Q7: The prototype can help identify reproducibility.	□	□	□	□	□
Q8: The feedback was helpful when reading and evaluating the paper	□	□	□	□	□
Q9: I trust the pipelines’s output when assessing reproducibility.	□	□	□	□	□

OPEN FEEDBACK:

Are there any important aspects of reproducibility you think the checklist missed?

In what ways did the prototype support or simplify your work?

Do you have any other comments or suggestions regarding the checklist and/or prototype?

Thank you for taking the time to complete the study and survey. Your feedback is invaluable in helping me enhance the pipeline. If you have any further comments or concerns, please feel free to reach out to me at:

domenik.kern@stud.uni-hannover.de

I appreciate your participation.

Sincerely,
Domenik Kern

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