Training Programmes on Writing with AI – but for whom? Identifying Students' Writer Profiles through Two-step Cluster Analysis

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Abstract: Generative AI has the potential to transform writing in schools and universities. This makes it necessary to develop training programmes for writing with AI, especially for students in teacher training. So far, however, little is known about the students' initial preconditions on which the trainings can be based upon. Evidence so far has come mainly from observational studies and questionnaire studies examining the frequency and type of AI use. However, the students themselves were not considered, nor the extent to which they can be categorised into groups. In other words, the focus has been on the writing rather than on the writers. To address this gap, the present article analyses data from a survey of N=505 students. To identify writer profiles, i.e. groups of students with comparable characteristics, we apply two-step cluster analysis. The students are clustered based on their use of AI for writing, as well as their level of awareness of AI applications, AI literacy, digital media literacy and writing-related self-concept. The results reveal four clusters, the two largest of which are characterised by the fact that students tend not to use AI, sometimes because they apparently have no awareness of AI, sometimes despite having such awareness. Merely one cluster, which describes 20% of the students, is characterised by regular use of AI for writing. The results therefore provide a useful insight for planning training in the context of university teaching.

Keywords: Artificial intelligence, writing with AI, future teachers, cluster analysis

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1. Introduction

Generative artificial intelligence (genAI) is said to have the potential for disruptively changing academic writing (Alier et al., 2024; Bhatia, 2023). In particular, the ability of AI to produce a superficially coherent text in a matter of seconds is often seen as a resource, from supporting students' writing to serving as a personal tutor (e. g. Jensen et al., 2024). At the same time, automatic text generation also raises concerns: Immediately after the release of ChatGPT, Anson & Straume (2022) anticipated that educators would fear that AI would, in the long run, take writing completely out of the hands of learners and with this may bring about the "end of education as we know it" (Williamson, 2023). In response to the widespread potential of AI on the one hand and the new challenges on the other, various institutions issued comprehensive recommendations on how to deal with AI in the education sector (e. g. UNESCO, 2021). In these, they emphasise the urgent need for the design of training programmes and learning opportunities on writing with AI for university students. However, empirical studies on which such programmes could be based remain scarce.

To get a first overview of how genAI is used in academic writing by students, initial questionnaire studies have been conducted in different countries (Barrett & Pack, 2023; Črček & Patekar, 2023; Helm & Hesse, 2024; Hoffmann & Schmidt, 2023; Kelly et al., 2023; Malmstrum et al., 2023; von Garrel et al., 2023; Welding, 2023). Additionally, first observational studies have been realised in which students were asked to write with AI (Fyfe, 2023; Tossell et al., 2024). The results of these studies are ambivalent: On the one hand, AI applications and, above all, OpenAI's ChatGPT are very well known amongst students (e. g. Malmstrum et al., 2023). On the other hand, familiarity with AI applications does not automatically lead to their use in the writing process. Rather, the use of AI applications in writing, if at all, is mainly limited to the planning phase (e. g. Helm & Hesse, 2024; Hoffmann & Schmidt, 2023; von Garrel et al., 2023). Moreover, it can be observed that writing with AI is neither faster nor easier in the students' perception (e. g. Fyfe, 2023; Tossell et al., 2024).

What all of the above studies have in common is that they address the ***frequency*** and ***types of AI use*** in writing. However, in the context of university teaching, the focus should not only be on different types of use, but also on the users themselves. This echoes van Waes (1992), who emphasised the need to differentiate between ***writing profiles*** and ***writer profiles*** in the context of the introduction of computers to writing (van Waes, 1992; van Waes, Luuk & Schellens, 2003). Writing profiles focus on differences in the writing process, while writer profiles focus on individual differences between writers. With regard to the demand for the development of training programmes, a differentiation of writer profiles seems of particular importance, as these profiles and their inherent characteristics can provide insights into the pedagogical approaches that may be most beneficial for students with varying needs (Kim, 2020; Pastor et al., 2007). These insights are in turn relevant, as learning opportunities that focus on the individual requirements of the students prove to be particularly effective (Kim, 2020; Korthagen, 2016; Kunter et al., 2011; Lipowsky & Rzejak, 2021).

One way of differentiating between writer profiles and thus finding different groups within the students, is to use cluster analysis. Cluster analysis describes the mathematical process of grouping sets of objects in such a way that the objects in one group are more similar to each other than to those in other groups, using algorithms. This method is common practise in higher education research in order to group people together on the basis of similar characteristics (e. g. Huberty et al., 2005). It therefore seems reasonable to apply a cluster analysis to identify writer profiles in the context of writing with AI.

Against this background this study will re-analyse data from a questionnaire study conducted among 505 university students. The data has already been analysed descriptively in a previous study (Helm & Hesse, 2024). The study revealed that although most of the students are aware of AI applications and especially ChatGPT, they only use them in a few writing activities beyond the planning of texts. These results were surprising given the extensive potential that AI applications are assumed to have for various writing activities. However, the limitation of the existing study (and numerous comparable frequency-based evaluations of student surveys) lies in the fact that a descriptive analysis of frequencies and mean values can barely take into account the potential heterogeneity of students. It could be disregarded that within the supposedly homogeneous mass of students, there are subgroups that differ from each other in their awareness and use of AI for writing. To address this, the prior analysis is comprehensively expanded in the present article in the form of a cluster analysis. As criteria for the cluster formation, the *usage of AI applications* for different sub-activities of writing, *awareness of AI applications*, *AI literacy*, *digital media literacy* and the *writing-related self-concept* are used. By using these factors, it is also possible to examine the extent to which the resulting groups and (i.e. writer profiles) differ in these personal characteristics, most of which are also targeted as key dimensions in training programmes.

In the following, this article will first present central research findings from international questionnaire studies on writing with AI, before introducing central categories for the cluster analysis. The results are then presented and analysed with regard to their didactic implications for higher education.

2. Literature Review

2.1 Usage of AI for writing in national and international student surveys

Attempts to chart the usage of AI applications for writing have primarily been made in the context of university teaching. Studies show a clear trend towards an increase in the use of AI-based tools among university students since the release of ChatGPT. Surveys conducted around or before March 2023 report that approximately 45% of students have already gained some experience with ChatGPT or similar AI applications (Črček & Patekar, 2023; Kelly et al., 2023; Welding, 2023). For September 2023, a study reports a slightly higher than average awareness of chat-based AI applications among students at a technical university (Balabdaoui et al., 2024). Subsequent studies indicate an increase of this proportion, with a slight majority of students (60–66%) having already worked with AI applications for their studies or in private (Hoffmann & Schmidt, 2023; Malmstrum et al., 2023; von Garrel et al., 2023). This trend appears to be largely continuing for 2024, as in recent studies less than 10% of students say that they have not yet had any experience with AI (Helm & Hesse, 2024; Tossell et al., 2024). The best-known AI application by far is always ChatGPT: Malmstrum et al. (2023) reported that a total of 95% of their students were familiar with ChatGPT, while only 38% were aware of Bing AI and 21% knew about Gemini. Similarly, von Garrel et al. (2023) found that among students using AI in their studies, 77.5% used ChatGPT, while only 2.9% were familiar with Bing AI. Comparable results are also provided by more recent surveys, in which DeepL and Grammarly follow in second and third place after ChatGPT with an awareness rate of around 57% and 62% respectively (e. g. Helm & Hesse, 2024).

However, the familiarity with AI applications (and ChatGPT in particular) does not automatically result in regular use for writing. Studies at several German universities showed that although 99% of students claim to be aware of ChatGPT, only between 29-60% of students say they use them ‘daily’ or at least ‘weekly’ (Hackl, 2024; Helm & Hesse, 2024). In earlier studies, around 25-35% of all students surveyed stated that they use AI tools at least “frequently” or even “very frequently’ (Hoffmann & Schmidt 2023, p. 5; Malmstrum et al. 2023, p. 6; von Garrel et al. 2023, p. 20–21). This is astonishing, as the picture is different for non-AI-based digital applications: For *google.translate*, for example, it can be shown that around 95% of all students state that they are familiar with this digital tool and 70% also state that they regularly use it to complete writing tasks (Malmstrum et al. 2023, p. 9).

If an attempt is made to identify specific use cases of AI applications for writing, all studies unanimously show that usage in the *planning phase* is most dominant (Hoffmann & Schmidt, 2023; Malmstrum et al., 2023; Tossell et al., 2024; von Garrel et al., 2023). In this phase, literature research, literature summary and providing topic information prove to be particularly widespread forms of use. Consistent with this, students consider the use of ChatGPT for brainstorming and text planning to be the (al)most ethically acceptable variant (Barrett & Pack, 2023; Črček & Patekar, 2023), while they often view ChatGPT as a "cheating tool" in other phases of writing (Tossell et al., 2024, p. 1076).

The use of AI in the *formulation phase*, i.e. the production of text in the narrow sense, is nevertheless widespread – albeit probably less common – as an application scenario. The information provided by students on the extent to which they use AI for text formulation varies considerably in some cases, which may also be due to the format of the questionnaire studies and the presumably influencing social desirability. In the study by Welding (2023), for example, 80% of the students surveyed stated that they used AI to formulate texts, while only 39% of the students in von Garrel et al. (2023) listed this type of usage. In Helm and Hesse (2024, S. 11), a comparable picture emerges: Only 13% of student state that they also occasionally have "whole text" written with AI.

The theoretical considerations suggest that, in addition to the use of AI applications for planning, the use of AI applications for ***revising text*** seems particularly promising. However, this cannot be clarified on the basis of the questionnaire studies conducted: A number of studies did not include any items aimed at this writing phase (e. g. Kelly et al., 2023; Welding, 2023) and therefore did not allow students to indicate this as a possible usage scenario. In the studies in which text revision was offered as an option, only a small proportion (5%) of students affirmed this usage (Črček & Patekar, 2023).

Overall, these studies provide the impression that the usage of AI – and this refers primarily to ChatGPT – can be described as highly selective: If AI is used for writing at all, it is more likely to be used for single writing activities within only a single writing phase, and here primarily in the planning phase. This is somewhat contradictory to both the theoretically assumed potential of AI and the fears expressed: This means that the data can neither confirm the assumption that students are fully utilising the potential of AI tools for writing, nor substantiate the concerns that students are handing over writing completely to AI tools.

However, it should be borne in mind that the questionnaire studies cited usually only present response frequencies and means for the whole sample. One advantage of this approach is that central tendencies become very clear. At the same time, however, possible differences within the sample tend to remain hidden. Structuring statistical methods, such as cluster analysis, can overcome this limitation and identify different groups of respondents.

2.2 Existing studies using cluster analysis

A first attempt to identify clusters of students based on personal characteristics in the context of writing with AI is provided by Burkhard (2022). He had students work with different AI applications (e. g. DeepL, Grammarly, Quillbot) and rate their usefulness on a five-point Likert scale. Clusters were formed based on their answers regarding the perceived usefulness of AI and the students' statements about their own attitudes and concerns towards AI. It was found that the frequency of AI use and scepticism towards AI were relevant factors for cluster formation, resulting in four clusters (Burkhard, 2022, S. 78). Two clusters are characterised by a limited use of AI, with one group (Cluster 1) being more sceptical of AI overall than the second group (Cluster 2). These two groups already account for a large proportion of the students surveyed, at 28% and 27% respectively. Burkhard identifies two further clusters as "problematic": ***non-skeptical frequent users*** (Cluster 3) and, conversely, ***skeptical non-users*** (Cluster 4). Students in Cluster 3 consider all tools (unreflectively) to be useful and have a fundamentally positive attitude towards AI. This is also the largest group, accounting for 33.5% of students. Students in Cluster 4, in contrary, consider the usefulness of AI applications to be fundamentally low and also express great skepticism. However, only 11% of students belong to this group. Upon closer examination, Burkhard can demonstrate that a large proportion (25%) of students in Cluster 4 are already in their second attempt of the first semester, indicating a tendency towards academic underperformance (Burkhard, 2022, S. 79). These students appear to be among the "low-performing students" with an overall low level of efficiency'.

This first and (to our knowledge) only cluster analysis of its kind already reveals two relevant aspects. Firstly, it shows that grouping students into clusters is a fruitful approach, as different and specific clusters emerge. These clusters of students in turn would certainly have to be addressed differently in a university teaching setting. Secondly, it shows that when forming clusters, personal characteristics – in the case of Burkhard (2022), number of semesters studied – must be taken into account. For the purpose of developing training programmes, however, it would be beneficial to include factors into a cluster analysis that could also represent potential target dimensions of the training programmes. This would enable statements to be made about the students' starting conditions and the training programmes to be adjusted accordingly. Therefore, the following chapter will examine which personal characteristics seem to be particularly relevant.

2.3 Relevant factors for describing writer profiles

To describe writing profiles, studies consulted suggest two types of relevant factors. Firstly, factors related to AI and its use, and secondly, factors related to personal (academic) performance and perception. Therefore, on the side of ***AI-related factors***, concepts such as ***AI literacy***, ***digital media literacy*** and the ***awareness of different AI applications*** come into play. On the other hand, ***writing-related factors*** are relevant, such as ***writing-related self-concept*** and the ***use of AI*** for different writing activities.

A first factor that seems relevant for distinguishing and describing clusters in the context of writing with AI is ***AI literacy***. The term AI literacy goes back mainly to Long and Magerko (2020), who define

> AI literacy as a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace (Long & Magerko, 2020, S. 2).

This construct is particularly interesting for cluster formation because it enables predictions about how efficiently students can use the functionalities of AI applications for writing. As Laupichler et al. emphasise, a "certain level of AI competence" (Laupichler et al., 2023, S. 1) is needed to gain an overview of the possibilities and limitations of AI applications. Students with little insight into how AI works are likely to struggle, for example, to develop functional prompts and adapting them for their own purposes (Zamfirescu-Pereira et al., 2023). With these less functional and unspecific prompts as a starting point, AI applications deliver low-quality output (Knoth et al., 2024, S. 8) that contain neither relevant information for writing nor can be integrated into their own text. If this experience had been repeated several times, it could lead to the overall impression that AI is of limited help for writing. However, the current state of AI literacy among university students remains largely unclear (Hornberger et al., 2023, S. 2), since existing research is mainly limited to the evaluation of training programmes aimed at promoting AI literacy (Kandlhofer et al., 2016; Kong et al., 2022) instead of evaluating AI literacy itself.

It also seems appropriate to assume ***digital media literacy***, which goes beyond the more specific AI literacy, as a relevant factor for cluster analysis. The term digital media literacy is not uniformly defined, but is often understood as the ability to access, understand and create media content (Penman, 2007, S. 1). Differences in digital media literacy are interesting for cluster analysis and the description of possible writer profiles, since it is to be expected that students with an affinity for technology will also be much more likely to use AI applications. Although there is currently no empirical evidence of a link between affinity for technology and the use of AI, at least Johnson et al. (2023, S. 81) show that self-perceived "technical competence" is a decisive factor for e. g. participation in digital media training courses. With this in mind, it is apparent that, for example, very low levels of digital media literacy are more likely to lead to disengagement from AI applications.

Another factor that seems relevant for cluster analysis is the students' ***awareness of AI applications***. It can be assumed that familiarity with a variety of AI applications also results in these being used in writing. It can be assumed that ChatGPT is known in many cases, as it is commonly demonstrated and tested as an accessible "prototype for AI applications" in numerous university introductory events, workshops and training courses (Nisak & Ishlahiyah, 2023). It is therefore particularly interesting to know how many AI applications students are aware of ***beyond*** ChatGPT.

Following Flower and Hayes (e. g. 1981), a distinction is usually made between the ***planning phase***, the ***formulation phase*** and the ***revision phase***. More recent works of writing research, however, emphasise the recursiveness of these phases, which tends to blur the boundaries between them (e. g. Philipp, 2015). On the one hand, this observation is particularly true for digital writing. On the other hand, in the context of writing with AI, clearly distinguishable phases emerge again (e. g. creating and entering the prompt, reading and reflecting on the AI output). However, instead of focusing on fixed phases (planning, formulating, revising) of writing, the focus can also be directed to different sub-activities of writing (e. g. structuring the text, summarizing literature), which in turn can only be roughly assigned to the (three) writing phases. If the sub-activities of writing are considered, it can then be asked to what extent these can already be supported by AI and to what extent students make use of AI support in these sub-activities. Since existing student surveys show that AI is used comparatively often for literature research, identifying topics or creating text modules and alternatives and less often for instance to formulate the full text or reviewing expression and style (e. g. Helm & Hesse, 2024; von Garrel et al., 2023), differences in the ***functions in writing*** among students are to be expected. It is possible that some groups use AI only in single sub-activities, while others use AI for many sub-activities (and thus consistently in all phases of writing).

Finally, another factor that is likely to be relevant and that could be used to distinguish between the clusters is the students' *writing-related self-concept*. It refers to their own assessment of the extent to which they can solve even complex writing tasks and writing-related problems. For example, Pajares (2003, S. 146) suggests that there is a close relationship between students' self-concept as writers and their actual academic writing performance. In relation to the use of AI for writing, it can be hypothesized that writers with a low writing-related self-concept may turn to AI for support more quickly and more often, whereas writers with a strong self-concept may want to write without support – or they want to write with the support of AI because they expect to be able to judge the quality of AI-generated texts well. Overall, it seems worthwhile to consider differences in writing-related self-concepts as factors in describing writer profiles of students.

3. Methods

3.1 Research Questions

Given the aim of clustering students into writer profiles in order to gain insights that are relevant for university teaching (e. g. to offer tailored training), two questions are particularly relevant:

- RQ1: Can the questionnaire data be transferred into clusters and which of the five factors are particularly important in the formation of clusters?
- RQ2: How can the emerging clusters be described and the resulting writer profiles interpreted?

Based on the findings gathered, it is to be expected that differences in the use of AI applications in particular will influence the formation of clusters. Recalling the concerns on the one hand that AI would completely take over writing for learners (Anson & Straume, 2022), and the results of Burkhard (2022) on the other hand, it can be assumed that a cluster with especially high usage of AI for writing will emerge. Given the results of the student surveys, it is also to be expected that an opposite group of students will be encountered who make little or very little use of AI applications.

3.2 Data Collection

In order to answer the research question, data was collected as part of a project focusing on writing with AI among future teachers. Although future teachers are a specific group of students, the results of an initial analysis showed parallels with the survey results of other national and international studies. For data collection a digital questionnaire was created using the SoSci Survey application. The questionnaire was mailed to 2,472 future teachers at a medium-sized German university in January and February 2024. To increase participation, the survey was advertised in lectures and combined with a lottery in which participants had the chance to win vouchers worth €150. Participation in both the survey and the lottery was voluntary. The survey was sent to future teachers of German, English, Physical Education, Physics and Geography. These subjects were chosen because they represent different areas, including language teaching, foreign language teaching, mathematics and science teaching. Participants were asked to choose one subject from a list at the beginning of the survey, as students in Germany usually study at least two subjects. All further questions in the survey should be answered with this subject in mind.

The raw data from the student survey can be found in the supplementary material (https://osf.io/pkxma).

3.3 Participants

Data from a total of 505 students was available for the reanalysis. Only participants studying to become secondary school teachers were included, as future kindergarten or primary school teachers were not trained at the university where the survey was carried out. Table 1 shows the subjects studied by the participants. The distribution of students who participated in the survey corresponds to the distribution of students enrolled in these subjects. In terms of gender, 328 students identified as female, 178 students identified as male, and 2 students identified as diverse. However, the latter group was not excluded due to its small size, which should be considered as a limiting factor when interpreting the results. In terms of age, the mean age of the participants was 22.92 years (*SD* = 2.90).

Table 1. Distribution of subjects studied between informants

(School) Subject Studied	Absolute Frequency	Relative Frequency
German (L1)	183	36.24
English (L2)	149	29.50
Geography	72	14.26
Sports/PE	71	14.06
Physics	30	5.94
	505	100.00

3.4 Items and Scales

For cluster creation (RQ1), a two-step cluster analysis was conducted using five variables: AI usage for writing, AI literacy, digital media literacy, awareness of AI tools and writing-related self-concept (s. Appendix A for scales).

To evaluate students' *AI literacy*, we used three items taken from a scale (Cronbach's α = .754) based on the TUCAPA model of AI literacy (Laupichler et al., 2023, S. 7). Students were asked to rate their proficiency concerning different facets of the model: technical understanding, practical application, and critical appraisal (e. g. I can identify limitations in AI and reflect on the dangers of its usage.“).

The students' *digital media literacy* was measured using a selection of items from scale for the self-assessment of digital competences of future teachers by Rubach and Lazarides (2019). These items focus, among other things, on the extent to which digital media can be used to search for and analyze information and files, to communicate with others and to solve problems.

The *awareness of AI tools* was recorded in such a way that the students were presented with a selection of different AI tools and asked to rate their frequency of use the in their studies ranging from *unknown* to *daily*, using a scale developed by von Garrel et al. (2023, S. 78). The selection of tools included both writing-specific tools with various functionalities (e. g. Grammarly, DeepL Write) and multi-purpose chatbots from OpenAI, Google, and Microsoft. For instance, we selected *Elicit* and *ResearchRabbit* to determine if students were aware of AI tools for scientific literature searches. We also included *PEER* or *fiete.ai* to identify if students already knew AI tools designed for educational contexts (see the supplementary material for the complete list). One possible limitation of the proposed tools is that – in particular – tools for correction and translation, such as Grammarly or DeepL, have been around for a long time and have only recently developed into AI-based tools. Accordingly, these may be more widely known in the first place. Nevertheless, we have mentioned them as they were repeatedly mentioned as relevant AI tools in the piloting phase of the questionnaire. To take students' overall tool awareness into account for the cluster analysis, we calculated the variable called "AI tool awareness". This variable counts the number of tools that students have *not* rated as *unknown*. This means that students with a low score on this scale have never heard of certain AI tools, while a high score indicates a broad knowledge of AI tools.

In order to determine to what extent and in what way students use AI applications for different *functions in writing*, they were presented with a series of statements to which they had to indicate their agreement on a five-point Likert scale ranging from 'strongly disagree' (=1) to 'strongly agree' (=5).. The statements focused on the different phases of writing, from planning (e. g. 'I use AI for literature research') and formulation (e. g. 'I use AI to create text parts/alternative formulations') to revision (e. g. 'I use AI to check formal correctness (spelling/citation)'). In order to be able to include the agreement with the statement in the cluster analysis, a new variable *writing functions* was calculated from the number and degree of approval. This variable counts the number of writing-related functions that students rated with a '4' or '5'. Acknowledging that we presented 10 different functions, the variable could take values ranging from '0' (AI tools were not frequently used for any of the writing functions) to '10' (AI tools were frequently used for all of the writing functions).

Finally, the study evaluates the participants' *writing-related self-concept* using a five-item scale (Cronbach's α = .817) based on a survey by Kruse et al. (2015, S. 24). As with the items on writing functions, the self-concept items were constructed to reflect different sub-activities of writing. For instance, students rated their confidence in 'reviewing a text' on a five-point Likert scale (example: I am confident in revising a text that has already been written.“).

To ensure the validity of the developed scales, they were first assessed independently by two professors from different universities who are distinguished experts in the field of writing research. In a second step, we conducted a think-aloud study with four future teachers from the University of Jena to evaluate the functionality and appropriateness of the items. Based on the expert and the future teachers’ feedback, we revised the questionnaire several times. In addition, we ensured the reliability of the questionnaire by using items that have proven reliable in other studies as part of factor or reliability analyses. To check whether the items were also reliable in the present context, we also calculated Cronbach's alpha. Table 1 provides an overview of the scales used, including sample items and Cronbach's alpha values. A complete list of all items can be found in the supplementary material (https://osf.io/qh587).

3.5 Statistical Analysis

To answer our research questions, a two-step-cluster analysis (TSCA) was conducted with SPSS V. 29 (IBM Corp. 2022). TSCA is based on two passes: The first pass divides the dataset into a coarse set of sub-clusters, while the second pass groups the sub-clusters into the desired number of clusters” (Gelbard et al., 2007, S. 158). The method offers several advantages over similar clustering techniques. For instance, it automatically selects the number of clusters based on statistical measures of fit (unlike k-means clustering which uses fixed numbers). Additionally, it is suitable for large datasets, as opposed to hierarchical clustering methods (Bacher et al., 2004; Chiu et al., 2001; Gelbard et al., 2007).

Table 2. Scales used and internal consistency

Scale	Items	Example (translation)	Internal consistency (Cronbach α)	Reference
Use of AI for different functions in writing	9	“I use AI applications to generate text modules / wording alternatives for my text.”	–	Self-developed based on Flower & Hayes 1981 and Philipp 2015
Awareness of different AI applications	13	“Indicate which AI applications you know, use or have tried out.”	–	Self-developed based on lists for most prominent AI applications
AI Literacy	3	I can identify limitations in AI and	.754	Laupichler et al. 2022; Long & Magerko 2020

		reflect on the dangers of its usage. ”		
Digital media literacy	10	“I can identify relevant sources and information in digital environments based on my search interest. identify and use digital environments.”	.765	A selection of items from Rubach & Lazarides 2019
Writing-related self-concept (focused on the process of writing)	5	I am confident in revising a text that has already been written. ”	.817	Kruse et al. 2023

The five previously mentioned variables were introduced as factors in the TSCA: ***Usage of AI for different writing functions***, ***AI tool awareness***, ***AI literacy***, ***digital media literacy*** and ***writing-related self-concept***. Log-likelihood was used as a distance measure and Schwarz's Bayesian Criterion (BIC) was applied as a clustering criterion to automatically determine the number of clusters.

Two parameters are crucial for assessing the quality of the cluster solution: the silhouette values and the importance of the predictors. The ***silhouette measures*** are decisive for the quality of the overall cluster solution. They can have values between -1 and +1, with higher values indicating better cluster solutions. A silhouette coefficient of 1 would mean that all cases lie directly in their cluster centers. A value of -1 would mean that all cases lie in the cluster centers of other clusters. A value of 0 means that, on average, the cases are equidistant from their own cluster center and the nearest neighboring cluster. According to Kaufmann and Rousseeuw (1990), three categories are distinguished for the interpretation of the silhouette values: “weak” values (-1<.2) do not show sufficient evidence for the presence of clusters, “fair” values (.2 < .5) show weak evidence for the presence of clusters and “good” values (> .5) show strong evidence for the presence of clusters. However, it should be noted that the silhouette values become smaller, especially when clusters are not perfectly separated from each other, but have a certain overlap. As this is generally expected in social science research, the value as such is less relevant than the question of whether the clusters found can be plausibly interpreted against the background of the research literature. The significance of the predictors was interpreted in order to assess the importance of the individual factors for distinguishing the clusters. It can assume values between 0 and 1, where 0 stands for a low and 1 for a high significance for the differentiation of clusters. This means that when interpreting the results, particular attention should be paid to those variables that have a high predictor significance.

4. Results

4.1 RQ1: Can the data be transferred into clusters and which of the five factors are particularly important in the formation of clusters?

The cluster analysis identified four clusters with an average silhouette measure of 0.3, which can be considered "fair" according to Kaufman & Rousseeuw (1990). As explained above, this indicates that although different clusters can be assumed in principle, they overlap in parts. However, as will be shown below, this is entirely understandable in view of the clusters found. When examining predictor importance (PI), the most significant factor in distinguishing between clusters is ***awareness of AI applications*** (PI = 1,00), followed by ***the use of AI for various writing functions*** (PI = 0,71), ***AI literacy*** (PI = 0,27), ***writing-related self-concept*** (0,22) and finally ***digital media literacy*** (0,07). All clusters are summarized in Fig. 1.

4.2 RQ2: How can the emerging clusters be described and the resulting writer profiles interpreted?

The largest cluster (Cluster 1) accounts for 34.3% of all students surveyed. With an average of 2.78, these students ***know*** comparatively few AI applications and use them for an average of 0.82 therefore slightly less than one (single) activity when writing. Students in this group have the lowest AI literacy (2.61) but the highest digital media literacy (4.37). This in particular shows that AI literacy and digital media literacy are separate concepts that neither merge nor necessarily go hand in hand. In addition, students in this cluster have the least pronounced writing-related self-concept (3.17). It can be synthesisedthat students in this group do not use AI when writing, regardless of their low writing-related self-concept and despite their high digital literacy and can therefore be labelled as ***non-AI writers***.

The second largest cluster (Cluster 2) comprises 29.7% of all students surveyed. These students in this cluster are familiar with slightly more than three AI applications on average (3.29) but use them for fewer sub-activities in the writing process (0.66) compared to the first cluster. However, they have a (significantly) higher level of AI literacy and the most pronounced writing-related self-concept of all four clusters. Based on these characteristics, it could be hypothesized that these students are consciously and deliberately refraining from using AI. Presumably, the perception of the limitations of AI could be at the forefront for students in this group. It is possible that these students have already had initial experiences with AI applications that were unsatisfactory, or that they have never progressed beyond the trial stage of several applications. They could therefore be described as ***AI-avoidant writers***.

The third cluster (Cluster 3) is characterized by the fact that the students are aware of an (enormous) number of AI applications (12.36). In percentage terms, 15.2% of students come closest to matching this user profile description. They state that they are familiar with an average of 12 or more applications, however, they only use AI support for slightly more than one writing-related sub-activity (1.32). Their AI literacy, their digital media literacy and their writing-related self-concept place them in the midfield compared to the other clusters. Therefore, it is the high level of awareness for application that makes this group stand out. One could speak of a group of *AI-enthusiasts*.

Students in the last group (Cluster 4, around 20% of the students) are familiar with a larger number of AI applications (5.14). Compared to the other clusters, they rate their AI literacy as the highest (3.72) and use AI applications for the most writing-related activities in comparison (more than 5). They ascribe themselves an average writing-related self-concept. It could be hypothesized that students with this user profile selectively choose applications from a rather broad knowledge of different AI applications that they consider supporting them in various writing-related activities. One could cautiously speak of *selective AI writers*.

Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Label	**non-AI writers**	**AI-avoidant writers**	**AI-enthusiasts**	**selective AI writers**
Description	are familiar with only a few AI applications and have the lowest AI literacy, but at the same time the highest digital media literacy, and barely use AI for writing (less than one writing-activity)	have the most pronounced writing-related self-concept and know a few AI applications, which they, however, hardly use for writing	are familiar with a large number (most) of AI applications, but still only use them to a limited extent for writing	have the highest AI literacy and know a decent selection of AI applications that they use in a variety of writing activities
Size	*N* = 173 (34.3%)	*N* = 150 (29.7%)	*N* = 77 (15.2%)	*N* = 105 (20.8%)
Inputs	awareness of AI-applications 2.78	awareness of AI-applications 3.29	awareness of AI-applications 12.36	awareness of AI-applications 5.14
	use of AI for functions in writing 0.82	use of AI for functions in writing 0.66	use of AI for functions in writing 1.32	use of AI for functions in writing 5.43
	AI literacy 2.61	AI literacy 3.52	AI literacy 3.43	AI literacy 3.72
	writing-related self-concept 3.18	writing-related self-concept 4.06	writing-related self-concept 3.71	writing-related self-concept 3.37
	digital media literacy 4.37	digital media literacy 3.94	digital media literacy 4.08	digital media literacy 4.13

Figure 1: Results of the cluster analysis. Darker colours indicate a higher predictor importance for clustering.

5. Discussion

The first observation of the cluster analysis is that the awareness of AI applications, which also was the strongest predictor in the cluster analysis, varies considerably between students: there are, firstly, a group of students who know only a few applications (Cluster 1 and 2), secondly, a group who have a standard repertoire of AI applications (Cluster 4), and, thirdly, a group whose awareness of AI applications clearly exceeds the previous groups (Cluster 3). This observation extends the existing findings of previous questionnaire studies among university students (e. g. Malmstrum et al., 2023; Tossell et al., 2024; von Garrel et al., 2023). These studies revealed that multi-purpose applications such as ChatGPT are already (very) well known among students, whereas specialised applications (e. g. PEER or fiete.ai/fellofish) are only known to a very limited extent. The results of the cluster analysis give reason to assume that this awareness of AI applications is unevenly distributed among students. Either students are basically familiar with only a few applications (presumably multi-purpose applications such as ChatGPT), or, in the opposite case, they are familiar with a whole range of different applications.

For the development of training programmes, it can be deduced that an introduction to different AI applications in the form of tool presentations and demonstrations is still indispensable: there are numerous students whose awareness of AI applications barely extends beyond ChatGPT. Conversely there are also students who are familiar with a wide range of AI applications – possibly more than many trainers themselves. In specific teaching situations, this can become a resource: Students who are familiar with a variety of applications could take on the role of tutors and present the applications they are familiar with and share their experiences of using them. Teachers on the training programme would need to encourage students to reflect on which of these applications might also be useful for writing.

A second observation is that students knowing numerous AI applications does not automatically lead to them also using these in a variety of ways in writing. This finding already emerged from the questionnaire studies (e. g. Kelly et al., 2023; Malmstrum et al., 2023; von Garrel et al., 2023) and initial experimental studies (Fyfe, 2023; Tossell et al., 2024). However, the cluster analysis makes it clear yet again that even an enthusiastic interest in AI, to the extent that almost all AI applications are known (Cluster 3), has little influence on their use for writing. On the contrary, students who actually use AI applications for writing (Cluster 4) are characterised by the fact that they know a solid selection of AI applications, but not an exuberant mass.

For the creation of training programmes, this implies that three different designs will probably have to be considered, each of which will address different starting points for the students. For students who already use AI in a variety of ways in their writing (Cluster 4), the training can be used to fine-tune their writing with AI in order to meet writing requirements in the "extreme forms of conceptual writing" (Steinhoff, 2007, S. 75), such as in term papers and theses. For students who already have a broad knowledge of AI applications but rarely use them for writing (Cluster 3), their previous writing experiences can be used as a starting point. It may be a practical approach to organise these students into small groups to work on specific writing tasks during the training, stopping at points of difficulty and discussing and reflecting with the trainer. Students in Cluster 2 already have a foundation in writing, so the entry point can be to introduce them to various AI applications and their potential to enhance writing. For their support, trainers should have a small selection of (tried and tested) writing scenarios available in the programmes, in which the support of AI applications seems to be particularly beneficial. These starting points are unlikely to be available for students in Clusters 1, where a training programme would be required to introduce them to writing with AI in a gradual and multi-perspective way (both from the writing perspective and from the AI perspective).

A third observation is that the present cluster analysis is only partially consistent with existing cluster analyses. Burkhard (2022), for example, also identified four clusters, but these included a large cluster in which students not only found 'all kinds' of AI applications useful but also used them (unreflectively) for writing. Only a smaller cluster of students were fundamentally sceptical about AI applications and refrained from using them in his analysis. In the present study, neither the perceived usefulness nor the scepticism towards AI was considered, but it is already apparent at the level of AI usage that the proportions appear to be different. In contrast to Burkhard's analysis, there is only a small cluster of students who are familiar with numerous AI applications and use them regularly for writing, but this is by no means a dominant group. Furthermore, these students are characterised by a high level of AI literacy and a pronounced writing-related self-concept. It could be assumed that these students make use of their knowledge and are not simply relying on AI without reflection. Conversely, the present analysis finds three clusters of students – and thus a clear majority – who do not use AI for writing. In Burkhard's study, in contrast, this was still a rather small group. He assumed that this cluster of sceptical users consisted mainly of students with low self-efficacy (ibid. p.79). However, the students in the present study who do not use AI for writing are characterised by a high level of writing self-concept, which is not in line with Burkhard's assumption. Accordingly, future studies should monitor the relationship between perceived usefulness, scepticism, writing-related self-concept and the actual use of AI for writing.

6. Limitations

The present study is limited by several factors: The first limitation is that all information on cluster-forming characteristics comes from the future teachers' self-assessments and may be strongly influenced by social desirability or the urge to provide socially acceptable answers, especially in view of the currently controversial topic of AI. Therefore, our analyses should be supplemented by cluster analyses based on more objective data from observations or tests in the future. A second limitation is that the data analysed was collected at only a single German university. Therefore, it cannot be ruled out that local effects and particularities are hidden in the data. However, the broad similarities between the data and those from other national and international surveys – as Helm and Hesse (2024) have already shown – suggest that these influences are minor.

Finally, while a cluster analysis aims to identify largely homogeneous subgroups, this does not mean that the resulting clusters nevertheless exhibit a certain degree of internal diversity. Within the clusters of students who tend to refrain from using AI for writing, there may still be completely different personal reasons for not using it. Likewise, students who use AI for several sub-activities in writing may still differ greatly in their strategic approach and, for example, use very different AI applications at different points in the writing process. Further process observations and interview data would be needed to clarify these questions.

7. Conclusion

The present research paper aimed to extend the existing body of research by re-analysing the results of a student survey in the form of a two-step cluster analysis. In this way, the observation in existing questionnaire studies that students are aware of AI applications but do not use them for writing was to be investigated by dividing the presumably heterogeneous group of students into clusters. It was first shown that awareness of (numerous) AI applications and the quantity of writing sub-activities for which they are used are the most relevant cluster-forming factors, whereas AI literacy, writing-related self-concept and digital media literacy only play a minor role in distinguishing clusters. It was then shown that the group of future teachers can be divided into four clusters, out of which three are characterised by a low use of AI applications for writing. In contrast, only one cluster of future teachers with a moderate awareness of AI applications is also characterised by using the application for several sub-activities of writing.

The overall impression is that the great disruption for writing (Alier et al., 2024; Bhatia, 2023) has not (yet) occurred when the data was collected (February 2024). The majority of students (Cluster 1 and 2) use AI in less than one sub-activity of writing – if at all, then probably for planning text. It should not be denied that AI affects the writing process, but to what extent this selective influence can be described as *disruption* is a matter of debate. In contrast, students who actually make use of AI applications in several sub-activities of writing (Cluster 4) are characterised by a pronounced writing-related self-concept. This might indicate that these writers are particularly capable of effectively integrating AI applications into their own writing process.

Looking ahead, the question remains why some students use AI for writing and others do not. For example, the extent to which individuals' actual writing skills influence the usage of AI applications has not been considered. In one direction, it is possible to hypothesise that advanced writers are more likely to be disillusioned by the results of AI applications and prefer to write for themselves. Conversely, a high level of writing competence could lead to the development of effective strategies for using AI in writing, so that novice writers are (quickly) overwhelmed by AI output and no longer use it in their writing. Ultimately, the causes can only be speculated on and remain to be analysed in future studies. It is possible that there are ethical and moral concerns that AI is a 'cheating tool', as Barrett and Pack (2023) found in their survey of students. Moreover, it is conceivable that the use of AI for writing entails more prerequisites than originally thought, so that students ultimately "think twice before letting the machine write for them" (Fyfe, 2023, S. 1401). Perhaps legal regulations and a lack of availability or affordability (paywalls) are also obstacles to its use. More detailed insights could be gained here, for example, by conducting interviews with students with different usage habits with regard to AI.

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