Generative AI at School

Insights from a study about German students' self-reported usage, the role of students' action-guiding characteristics, perceived learning success and the consideration of contextual factors

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For any questions, feedback and recommendations please contact the authors directly.

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Summary

The present study is one of the first to investigate the use of generative AI, such as ChatGPT and others, in German schools. The study is explorative in nature and focuses on the use of generative AI from the students' perspective. The aim of the study is to investigate whether, to what extent and for which tasks students use generative AI. We also examine whether and what kind of relationships exist between the intensity of students' use of generative AI and action-guiding characteristics considered crucial in digitalized educational environments, such as social perception of intelligent technology, need for cognition, self-efficacy expectation, technostress, and technology commitment. In addition, we analyze how contextual factors such as social support from school and parents, as well as facets of parents' social status, are related to students' AI use frequency. Finally, we examine whether AI use is correlated with students' self-perceived AI-related learning success and how it can be grouped into higher-order concepts.

We conducted a quantitative analysis on a dataset (N=226) collected through an online survey between March and July 2023 with students aged 15 to 19. The results show that there are differences in generative AI usage frequency for different types of tasks. It is expected to become increasingly used by students for doing homework, writing texts, and supporting creative processes such as brainstorming and research. Students' self-efficacy expectation for being able to do something useful with this technology seems to play an important role in the context of generative AI use. At the same time, we see that students' perceptions of technology-related stress can be important when using generative AI. The results also show that social support from educational institutions and parents plays an important role in the use of generative AI. In contrast, the levels of parents' education as well as academization are negatively correlated to generative AI use, particularly in the context of social media use. In addition, students' social perceptions of AI tools, especially regarding the perception of generative AI as partially human-like (anthropomorphic), seem to be relevant when using generative AI. Interestingly, a higher frequency of generative AI usage is associated with a lower level of cognitive engagement as well as belief in technological competence among students. However, higher levels of students' self-perceived learning success are associated with a higher intensity of generative AI usage. Finally, we grouped the here developed 31 types of generative AI use into four higher-order concepts of generative AI use, which we named "performing standard tasks," "exploring new opportunities," "improving one's own work results," and "inspiring creative thinking."

With this study on the use of generative AI from the students' perspective, we aim to contribute to a better understanding of how generative AI can change young people's learning processes today and in the future. In the final discussion section, we argue that the results of our analysis can contribute to the development of sustainable approaches on ways to transform the educational system so that it empowers young people in our technologically permeated, knowledge-intensive society to become creative, reflective, and mindful citizens of the future society.

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1. Introduction

Generative AI tools such as ChatGPT, Google Bard, and others are having a profound impact on the education sector (Su & Weipeng, 2023). While these novel tools and technologies can be seen as a powerful driver for the digital transformation of the education system, little is known about their actual use in education. Recent studies have revealed that learners, as well as teachers or lecturers are increasingly using GPT-based tools during teaching and learning processes (Müller et al., 2023). However, there is a lack of systematic knowledge about how students at German schools use generative AI in or for school, and how different ways of using generative AI might be related to students' individual action-guiding characteristics, e.g. regarding their commitment to smart technologies. In addition, more empirically based research is needed on the relationships between how generative AI is used and other contextual factors, such as social status or social support.

Research in the field of digital transformation has already shown that people's readiness to use technology, also referred to as technology commitment, which consists of the three dimensions of technology acceptance, technology competence, and technology control belief, may be relevant for the way of using the latest digital tools and technologies (Davis, 1989; Neyer & Felber, 2012).

Furthermore, the perception of AI-based tools and intelligent technology as social, cooperative and anthropomorphic is considered to be related to the way people use technology (Mandl et al., 2022, 2023). As generative AI is often perceived as a tool that may reduce users' cognitive engagement such as critical thinking (e.g. Hahn & Lee, 2017; Yoon & Lee, 2021), we also find it fruitful to explore how students' need for cognition relates to the use of generative AI. Since self-efficacy is also known to play a role in technology use (e.g. Ellen et al., 1991; Kulviwat et al., 2014), we find it crucial to investigate how AI-related self-efficacy expectations relate to students' generative AI usage. Another crucial aspect is technostress, which can be caused by the demands of using digital tools (e.g. Tarafdar et al., 2011). In the study, we investigate whether technostress plays a significant role regarding the use of generative AI by students at school.

In addition to these aspects, we find it highly relevant to investigate aspects related to equity in education, as generative AI tools, like other digital technologies, may contribute to inequality in terms of young people's future opportunities (OECD, 2018, 2023). In our study, we want to investigate more specifically how the social status of students' family environment is related to the usage practices of generative AI in learning and educational contexts. In addition, we seek to provide a more empirically grounded understanding of the role of both parental and schools' social support in relation to generative AI usage practices. We argue that these contextual factors should also be considered as crucial aspects of technology use, especially with regards to students at school.

Finally, we argue that students at school may also be motivated by the added value of the specific ways of using generative AI, particularly in terms of the efficiency of their own learning processes as well as the efficiency in terms of outputs such as grades they receive at school.

While we are among the first to conduct quantitative research in a field that is undergoing high levels of dynamic change and development, we are fully aware of the exploratory nature of this study. Based on our research motivation and the brief conceptualization above, we seek to provide insights into the five key research questions:

RQ1. How extensive is students' use of generative AI in school and beyond?

RQ2. What is the relationship between generative AI use and students' action-guiding characteristics?

RQ3. What is the relationship between generative AI use and contextual factors?

RQ4. What is the relationship between generative AI use and self-perceived learning success?

RQ5. How can generative AI use be grouped into higher order concepts?

During the present study we combine a specific set of measurement instruments and scales which are both, based on questions and instruments developed and critically reflected by our research experts and well-established scales from scientific literature. Section 2 contains the detailed information about our methodological approach. The insights about the sample structure and the descriptive statistics is presented in section 3. In Section 4 statistical results and findings including information about the data analysis procedures are presented. In section 5 we summarize the findings, discuss the main results and present some general recommendations. Finally, we find it important to share our critical thoughts about the limitations of this study including the overall approach in section 6.

2. Methodology

We conducted a quantitative study on a dataset collected through an online survey between March and July 2023 with 15-19 years old students from four German high schools. The sample size is N=226. To answer the research questions RQ1 to RQ5, we adapted correlation analysis as well as an exploratory factor analysis (EFA). The variables and scales used in our analysis are described in detail below.

2.1 Generative AI use

We generated the following set of 31 items (see Table 1) to find out for which tasks or objectives and at what intensity students use generative AI for or at school. The 31 items were developed and finalized during an iterative process of workshops and discussion together with teachers from German schools. We measured the usage intensity by asking the survey participants how often they use generative AI to perform each of the 31 tasks. The answers were measured on a 5-point scale (1 = never, 2 = rare, sometimes = 3, often = 4, very often = 5). All 31 ways of generative AI usage are presented in Table 1.

Table 1: Items for measuring the ways of generative AI usage

No.	Ways of generative AI use	No.	Ways of generative AI use
1	*Doing homework*	17	*Writing a post*
2	*Writing texts*	18	*Correcting an e-mail*
3	*Creating a text quickly*	19	*Creating an outline for a text*
4	*Translating*	20	*Completing sentences*
5	*Playing games*	21	*Creating lyrics*
6	*Chatting*	22	*Solving math exercises*
7	*Programming*	23	*Creating a social media post*
8	*Giving feedback on someone else's solution*	24	*Improving the language of my own texts*
9	*Getting feedback on my own solution*	25	*Researching sources*
10	*Supporting brainstorming*	26	*Finding literature*
11	*Writing texts for blogs or forums*	27	*Questioning texts*
12	*Checking the spelling of my own texts*	28	*Getting inspiration*
13	*Revising the content of my own texts*	29	*Getting advice*
14	*Performing research*	30	*Chatting with literary characters or historical persons*
15	*Answering teachers' questions*	31	*Creating tables, charts or figures*
16	*Writing a blog*		

2.2 Students' action-guiding characteristics

Social perception of generative AI (SOC, COO, ANT)

We measure the social perception of generative AI by adapting the social perception of robots scale (SPRS) (Mandl et al., 2022) to generative AI. The SPRS scale is an 18-item questionnaire to assess humans' social perception of their robotic counterparts. The scale consists of the three variables social (SOC), cooperative (COO) and anthropomorphic (ANT). It measures the strength of humans' perception of the robot's social, cooperative and anthropomorphic traits on a scale from one to five, where one indicates a high rating and five a low rating. We adapted the SPRS to generative AI by modifying the item moves smoothly – moves rigidly to eloquent – not eloquent. Additionally, for better interpretation of our results we reversed the polarity of the scale, such that one indicates a low rating and five a high rating.

Technostress (ADM, NSM)

Technostress indicates stress caused by the inability to cope with the demands referring to the usage of digital tools (Tarafdar et al., 2011). The scale, we use in this work was developed to measure university students' technostress (Wang et al., 2020). It consists of the two dimensions abilities – demands misfit (ADM) and needs – supplies misfit (NSM). ADM addresses the gap between individuals' abilities and skillsets required to participate in technology-enhanced learning and the time and effort available to them. NSM refers to the students' gap between the needs for improved learning experience through digital technologies and the technology-enhanced learning satisfaction (Wang et al., 2020). The scale consists of eight items that are measured on a 5 point consent scale with 1= "completely disagree", 2= "disagree", 3= "undecided", 4= "agree", 5= "completely agree".

AI-related self-efficacy expectation (ASE)

Self-efficacy expectation is defined as an individuals' competence expectation to deal with difficulties and obstacles in daily life (Bandura, 1986). Thus, with AI-related self-efficacy expectation (ASE) we mean the students' competence expectation to deal with the demands caused by using generative AI. We measure AI-related self-efficacy expectation by an adaption of the German ASKU (Beierlein et al., 2014). The scale is a 5-point self-assessment scale, 1 (Not applicable at all) to 5 (Fully applicable).

Need for cognition (NFC)

Need for cognition (NFC) describes the person's individual ability to engage in or enjoy cognitive endeavors (Cacioppo et al., 1984). Therefore, NFC intends to explain students' commitment to cognitively challenging tasks. The NFC-teens scale (Preckel, 2016) used in the present work is designed to measure NFC for older kids (approx. older than 10 years). It consists of 19 items and is measured on a 5 point Likert-scale with the response options 1 (Not applicable at all) to 5 (Fully applicable). For evaluation, the points are added and can take on values between 19 and 95.

Technology Commitment (TAC, TCP, TCO)

The scale for technology commitment (Neyer et al., 2016) is based on the concept of technology readiness (Davis, 1989). The successful use of technology depends on attitudes as well as competence and control beliefs (Neyer & Felber, 2012). The scale consists of twelve items divided between the three factors technology acceptance (TAC), technology competence (TCP) and technology control (TCO) conviction. The items address the users' very personal attitudes towards and use of modern technology. It intends to predict the successfulness use of novel technologies. The instrument is a five-point scale with options 1 (Not applicable at all) to 5 (Fully applicable).

Students' self-perceived AI-related learning success

This scale is a self-developed assessment tool which is supposed to provide insights about how students judge their own learning success at school. The instrument consists of the 5 question items "I use AI-based text generators very successfully", "AI-based text generators help me to improve my academic performance", "Learning is easier for me when I can use AI-based text generators", "My school grades have improved since I started using AI-based text generators" and "With the help of AI text generators, I am able to complete my schoolwork faster and more efficiently". Answers were given on a 5-point Likert scale from 1 (Not applicable at all) to 5 (Fully applicable).

2.3 Contextual factors

As contextual factors we measure social support for using generative AI provided by the educational institution and / or parents and facets of the so called social status which we are gathering by asking for parents' school education and profession levels as well as parents' financial situation.

Social support for AI usage provided by the educational institution (SOE)

Since support provided in form of encouragement through teachers to use generative AI or provision of suitable IT-infrastructure could encourage students to use generative AI in or for school we develop a variable to assess how high students rate their school's social support for using generative AI. The item is the following: "At school, I am supported in the use of generative AI tools." Answers are given on a 5-point Likert-scale from 1 (Not applicable at all) to 5 (Fully applicable).

Social support for AI usage provided by parents (SOP)

Social support provided at home by parents could also play a crucial role for the students' usage intensity of generative AI at school. Thus we developed the following item to measure social support for AI usage provided by parents (SOP): "My parents support me in using generative AI." The item is measured on a 5-point Likert-scale from 1 (Not applicable at all) to 5 (Fully applicable).

Parents' school education level (PAS)

The parents' educational level is measured by asking survey participants for the highest school-leaving certificate of parent A and parent B. The scale is a 4 - point scale with possible answers 1 = "not known", 2= "no school qualification", 3 = "secondary school diploma (Haupt- / Realschulabschluss)" and 4 = "high school diploma" (Fach-, Hochschulreife)". Finally, PAS is calculated by creating the sum over the educational level of parent A and parent B, where cases with the value 1 have been omitted since they are irrelevant for the ranking of the educational level.

Parents' professional level (PAP)

Parents‘ highest professional level is measured by the variable parents' professional qualification (PAP). Again, the students are asked about the highest professional qualification of parent A and parent B respectively. Possible answers are: 1 = "not known", 2= "no professional level", 3 = "professional training (Berufsausbildung)", 4= "Technician (Meister / Techniker)", 5 = "Academic". Finally, PAP is calculated equally to PAS.

Parents' financial situation (PAF)

The financial situation at the student's home is measured by the variable parents‘ financial situation (PAF): "How do you rate the financial situation at your parents' home?". The answers are given on a 5-point scale from 1 (significantly below average) to 5 (significantly above average).

3. Sample characteristics and descriptive statistics

Data was collected through an online survey conducted in Germany from March to July 2023. Students from four German schools participated in the survey. Three of the schools were high schools (Gymnasium) and one was a comprehensive school (Gesamtschule). A total of 226 students between the ages of 15 and 19 belonging to the upper school (grades 10 to 13) participated in the survey. Descriptive statistics for the sample are presented in Table 2.

Table 2: Descriptive statistics of the sample

<table>
<tr><th>Gender</th><th>male</th><th>female</th><th>divers</th><th>Not specified</th></tr>
<tr><td>Number /%</td><td>98 / 43.4</td><td>117 / 51.8</td><td>6 / 2.7 %</td><td>5 / 2.1 %</td></tr>
<tr><th>Age
(years)</th><th>15</th><th>16</th><th>17</th><th>18</th><th>19</th><th>Not specified</th></tr>
<tr><td>Number /%</td><td>54 / 23.9 %</td><td>95 / 42.0 %</td><td>57 / 25.2 %</td><td>19 / 8.4 %</td><td>1 / 0.5 %</td><td>--</td></tr>
<tr><th>Grade</th><th>10</th><th>11</th><th>12</th><th>13</th><th>Not specified</th></tr>
<tr><td>Number /%</td><td>151 / 66.8 %</td><td>63 / 27.9 %</td><td>10 / 4.4 %</td><td>2 / 0.9 %</td><td>--</td></tr>
<tr><th>Parents' school education level</th><th>No school qualification</th><th>Secondary school diploma</th><th>High school diploma</th><th>Not specified</th></tr>
<tr><td>Number /%</td><td>11 / 4.9 %</td><td>53 / 23.5 %</td><td>150 / 66.4 %</td><td>12 / 5.2 %</td></tr>
<tr><th>Parents' professional level</th><th>No professional level</th><th>Professional training</th><th>Technician</th><th>Academic</th><th>Not specified</th></tr>
<tr><td>Number /%</td><td>9 / 4.0 %</td><td>56 / 24.8 %</td><td>55 / 24.3 %</td><td>88 / 38.9 %</td><td>18 / 8.0 %</td></tr>
<tr><th>Parents' financial situation</th><th>significantly under average</th><th>Rather under average</th><th>Average</th><th>Rather above average</th><th>Significantly above average</th></tr>
<tr><td>Number /%</td><td>3 / 1.3%</td><td>18 / 8.0%</td><td>104 / 46.0%</td><td>81 / 35.8 %</td><td>20 / 8.9 %</td></tr>
</table>

4. Findings

4.1 Frequency of students' generative AI usage at school and beyond (RQ1)

Students were asked about their individual frequency of using generative AI on a 5-point scale from "never" to "very often" for all 31 different areas (Table 1). The results of the frequencies of the students' ways of using generative AI are shown as percentages in Figure 1. These results show some profound differences between the different ways of using generative AI. For example, in our sample, more than 70% of the students never use generative AI for programming, writing texts for blogs or forums, writing a post or creating a social media post, creating lyrics, or finding literature. For writing a blog, 82% of students said they would never use generative AI. For homework, which is clearly a school-related task, 37% never use generative AI, 23% rarely use it, 28% sometimes use it, 10% often use it, and 2% use it very often. The tasks of writing texts, creating a text quickly, translating, and supporting brainstorming show similar distributions to the task of doing homework. For research, even 21% of the students seem to use generative AI often and 11% very often. In summary, we can conclude that the use of generative AI in or for school is potentially of growing importance, especially for specific school-related tasks, and that there are clear differences in frequency between different ways of using generative AI.

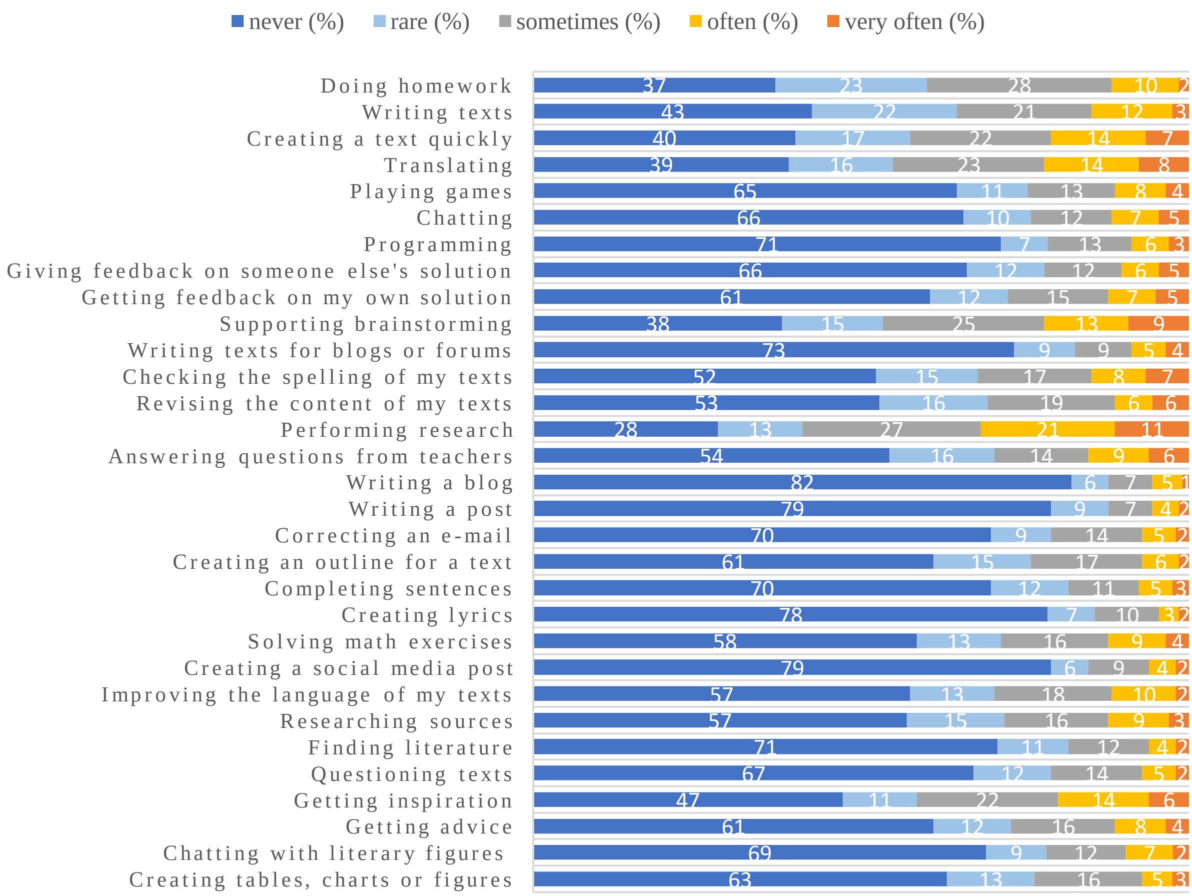

Figure 1: Frequencies of students' ways of using generative AI

4.2 Relationship between generative AI usage and action-guiding characteristics (RQ2)

Research Question 2 focuses on the relationships between students' use of generative AI and a set of students' action-guiding characteristics. The action-guiding characteristics we consider in our study are social perceptions of generative AI, technology commitment, students' technostress, AI-related self-efficacy expectations, and need for cognition. Table 3 below provides an overview of the scale metrics, including Cronbach's alpha and mean scores. Cronbach's alpha (Cronbach, 1951) is a widely used measure for construct's reliability. Usually, a value of 0.7 or higher is seen as an indicator for a good reliability of a scale (Taber, 2018).

Table 3: Metrics of the scales of students' action-guiding characteristics

Action-guiding characteristics	Sub dimension	Abbrev.	Min	Max	Mean	SD	Cronbach's alpha
Social perception of generative AI	social	SOC	0.0	5.0	3.24	.75	.84
	cooperative	COO	0.0	5.0	3.56	.83	.78
	anthropomorphic	ANT	0.0	5.0	2.55	.72	.83
Technostress	Abilities-demands misfit	ADM	1.0	4.0	2.27	.76	.84
	Needs-supplies misfit	NSM	1.0	4.43	2.37	.74	.80
AI-related self-efficacy expectation		ASE	1.0	5.0	3.10	1.06	.87
Need for cognition		NFC	38.0	72.0	57.81	5.00	.84
Technology commitment	Technology acceptance	TAC	4.0	20.0	12.6	3.41	.76
	Technology competence	TCP	6.0	20.0	16.35	3.43	.85
	Technology control	TCO	5.0	20.0	13.43	3.01	.72

To examine relationships between students' action-guiding characteristics and generative AI use, we test for bidirectional correlations between these variables (Spearman correlations). The correlation values are shown in Table 4. The results show some positive correlations between perceiving generative AI as social, which means, for example, perceiving it as polite or courteous (Mandl et al., 2023), and the AI use for doing homework, writing texts, and supporting brainstorming. At the same time, there is a negative correlation with writing a post, creating a social media post, and chatting with literary characters.

For perceiving generative AI as being cooperative (COO), which means perceiving AI as e.g. hardworking, activating, selfless (Mandl et al., 2023), we also found positive correlations with doing homework and writing texts. There are negative correlations between COO and use for chatting, writing blogs or posts, correcting emails, creating lyrics, creating social media posts, finding literature, and chatting with literary or historical figures.

Regarding students' perceptions of generative AI as anthropomorphic (ANT), e.g., as real, warm, or organic (Mandl et al., 2023), we see in Table 4 that 30 of the 31 different uses of generative AI have a positive correlation, while most of the correlation values are highly significant. The use for doing homework, getting advice, writing texts, or creating tables, charts, and figures show the highest positive correlations. Translating has no significant correlation and there are no negative correlations for ANT.

Table 4: Correlation between students' action-guiding characteristics and generative AI usage

Ways of generative AI use	**Students' action-guiding characteristics**									
	SOC	COO	ANT	ADM	NSM	ASE	NFC	TAC	TCP	TCO
Doing homework	.19**	.15*	.38**	.04	.00	.63**	-.22**	.08	-.02	-.01
Writing texts	.17*	.15*	.35**	.09	.03	.55**	-.22**	.16*	-.06	.03
Creating a text quickly	.11	.09	.29**	.07	.06	.58**	-.25**	.24**	-.05	.03
Translating	-.11	-.06	.03	.16*	.09	.12	-.23**	-.02	-.21**	-.19**
Playing games	-.11	-.07	.16*	.26**	.17*	-.02	-.19**	.05	-.33**	-.09
Chatting	-.11	-.16*	.20**	.37**	.30**	.08	-.26**	.013	-.35**	-.12
Programming	.04	.00	.31**	.15*	.09	.19**	-.04	.20**	-.21**	.02
Giving feedback on someone else's solution	-.04	-.14	.31**	.35**	.24**	.19**	-.17*	.14	-.34**	-.12
Getting feedback on my own solution	.05	-.06	.32**	.23**	.12	.23**	-.07	.23**	-.29**	-.01
Supporting brainstorming	.18*	.12	.29**	-.01	-.10	.50**	-.06	.28**	-.04	.10
Writing texts for blogs or forums	-.06	-.10	.28**	.38**	.31**	.15*	-.22**	.04	-.39**	-.14*
Checking the spelling of my texts	.08	-.02	.26**	.19**	.06	.18*	-.05	.05	-.22**	-.03
Revising the content of my texts	.13	.06	.27**	.13	.04	.34**	-.09	.19**	-.18*	-.04
Performing research	.12	.11	.18*	.03	-.02	.52**	-.13	.11	-.06	.00
Answering questions from teachers	.000	-.03	.27**	.12	.06	.34**	-.23**	.18*	-.15*	-.03
Writing a blog	-.09	-.28**	.25**	.43**	.37**	.03	-.28**	-.04	-.39**	-.19**
Writing a post	-.16*	-.29**	.23**	.42**	.32**	.02	-.23**	.02	-.41**	-.18*
Correcting an e-mail	-.10	-.19*	.24**	.26**	.18*	.09	-.14*	.02	-.35**	-.16*
Creating an outline for a text	.00	-.08	.28**	.19**	.12	.34**	-.19**	.14	-.22**	-.12
Completing sentences	-.07	-.10	.30**	.31**	.20**	.18*	-.23**	.07	-.30**	-.12
Creating lyrics	-.13	-.23**	.32**	.36**	.29**	.03	-.14*	-.01	-.36**	-.16*
Solving math exercises	.00	-.06	.29**	.26**	.17*	.29**	-.24**	.09	-.29**	-.06
Creating a social media post	-.18*	-.28**	.25**	.47**	.28**	.02	-.24**	-.04	-.35**	-.21**
Improving the language of my texts	.08	.07	.34**	.17*	.11	.36**	-.10	.16*	-.22**	-.01
Researching sources	-.06	-.10	.22**	.18*	.11	.26**	-.20**	-.02	-.17*	-.26**
Finding literature	-0,11	-.26**	.20**	.27**	.17*	.11	-.15*	.03	-.32**	-.22**
Questioning texts	-.03	-.14	.29**	.19**	.14	.26**	-.13	.20**	-.22**	-.06
Getting inspiration	-.02	-.06	.24**	.07	.04	.39**	-.11	.15*	-.03	.05
Getting advice	.01	-.07	.37**	.15*	.12	.32**	-.16*	.22**	-.16*	-.07
Chatting with literary characters	-.17*	-.20**	.27**	.31**	.24**	.07	-.19**	.06	-.32**	-.08
Creating tables, charts or figures	.04	-.04	.35**	.18*	.11	.23**	-.10	.19**	-.18*	-.04

*: significance of bidirectional correlation p < 0.05

**: significance of bidirectional correlation p < 0.001

SOC = social, COO = cooperative, ANT = anthropomorphic; ADM = Abilities-demands misfit, NSM = Needs-supplies misfit; ASE = AI-related self-efficacy expectation; NFC = need for cognition; TAC = technology acceptance, TCP = technology competence, TCO = technology control

The first sub-dimension of technostress, called abilities-demands misfit (ADM), which refers to a student's perception or feeling that he/she cannot meet the demands of technology-enhanced learning based on his/her own abilities, skills, and investment of time and effort (Wang et al., 2020, p. 99), shows a number of positive correlations with 23 of the 31 ways of using generative AI. The strongest and highly significant correlations are between ADM and creating a social media post, writing a blog, writing a post, and writing text for blogs or forums. There are no significant negative correlations.

The second subdimension of need-supply mismatch (NSM) as part of students' technostress is related to the situation where technology-enhanced learning does not meet students' needs and preferences for learning (Wang et al., 2020, p. 99). As shown in Table 4, there are positive correlations between NSM and 12 out of 31 ways of using generative AI. The strongest positive correlations appear between writing a blog, writing a post, writing texts for blogs and forums, and chatting. As with ADM, there are no significant negative correlations for NSM.

Regarding AI-related self-efficacy expectation (ASE) in our sample, there are strong and highly significant correlations with doing homework, creating a text quickly, writing texts, and doing research. Significant and highly significant correlations are found between 21 of the 31 different ways students use generative AI and ASE. No significant negative correlations are found for our sample. Overall, the strongest positive and highly significant correlation of .63** is between ASE and doing homework.

Students' need for cognition (NFC), which represents students' engagement and enjoyment of effortful cognitive endeavors (Cacioppo et al., 1984, p. 306) and thus their cognitive engagement, is significantly negatively correlated with a number of generative AI uses. There are a number of correlations associated with using generative AI not only for school-related tasks, but also in extracurricular contexts, such as writing a blog or a post. However, there are also negative correlations with the use of generative AI specifically for school-related tasks, such as writing text quickly, translating, doing homework, or solving math problems. There are no significant positive correlations between NFC and the use of generative AI in our sample.

For students' technology engagement, which is related to the three components of technology acceptance (TAC), technology competence (TCP), and technology control (TCO), there are significant positive (TAC) as well as negative (TCP & TCO) correlations in our sample. TAC is significantly positively correlated with writing texts, creating a text quickly, programming, getting feedback on my own solution, supporting brainstorming, revising the content of my texts, answering teachers' questions, improving the language of my texts, questioning texts, getting inspiration and advice, and creating tables, charts, or figures. Correlation values range from .15 to .28, which is not very high compared to other variables examined in the study. There are a number of significant negative correlations between TCP and most types of generative AI use, except for doing homework, writing texts, creating a text quickly, supporting brainstorming, doing research, and getting inspiration. The highest absolute values equal to or greater than .39 are between TCP and writing text for blogs and forums, and writing both a blog and a post. There are also some negative significant correlations between TCO and the tasks translating, writing texts for blogs and forums, writing a blog or post, correcting an email, creating lyrics, creating a social media post, researching sources, and finding literature. However, the absolute values of the correlations are lower than those for TCP. Among the three components of students' technology engagement, TCP is correlated with most of the ways of using generative AI with the highest absolute values.

Based on these results regarding RQ2 on the relationship between the use of generative AI and a number of students' action-guiding characteristics discussed as relevant as some of the key aspects during the digital transformation and future education, we found strong support for our assumption that there may be highly significant correlations to the different ways of using generative AI. One aspect we find very interesting is that the perception of generative AI as anthropomorphic may play an important role for or during the use of these technologies. The second aspect we found highly relevant for research and practice is that AI-related self-efficacy expectations can be assumed to be a very important aspect for using generative AI. In addition, students' perceived technostress may play an important role for certain usage scenarios. Furthermore, the fact that students' need for cognition is negatively correlated with a number of different ways of using generative AI may be perceived to be worrying, as certain ways of using generative AI for short-term improvements may sacrifice students' future competencies in the areas of learning, adaptability, or improvisation. We argue that a potential risk of the general availability and even further improvement of these kinds of AI-based tools may go hand in hand with a reduction in cognitive engagement and enjoyment at school and after school, as shown by the results in Table 4 for the variable NFC. However, further empirical research on the basis of longitudinal studies, should be conducted to support this assumption.

Furthermore, we find it very interesting that there are positive correlations for students' technology acceptance as one variable of technology commitment, but especially for technology competence conviction there are many highly significant negative correlations. One possible reason for this can be seen in the differences between technology acceptance and technology competence conviction. TAC is rather concerned with the development of an intention for using a technology based on ease of use and usefulness while TCP represents an individual's subjective expectation of possible courses of action in technology-related situations (see Neyer et al., 2016, p. 88). The later has a more cognitive orientation which may explain to the differences in our results.

4.3 Relationship between generative AI usage and contextual factors (RQ3)

To answer our third research question about possible relationships between students' generative AI use and contextual factors, we considered five contextual variables representing social support for AI use by the educational institution as well as by parents, and social status measured by a ranking of parents' school education levels, parents' professional qualifications, and parents' general financial situation (see Table 5). We also provide some descriptive statistics for these variables, including the minimum, average, and maximum values. The values presented in Table 5 show that, on average, students perceive support from the educational institution as well as parents to be lower than the mean of the scale from 1 to 5. The mean for social status shows that students rate their parents' social status higher than the mean of the scale used in the survey (Table 5).

Table 5: Descriptive metrics of contextual factors

Contextual factor variable		Abbrev.	Descriptive metrics		
			Min	Mean	Max
Social support for AI usage provide by educational institution		SOE	1.0	2.3	5.0
Social support for AI usage provided by parents		SOP	1.0	2.0	5.0
Social status	Parents’ school education level (ranking)	PAS	4.0	7.2	8.0
	Parents’ professional level (ranking)	PAP	4.0	8.2	10.0
	Parents’ financial situation (ranking)	PAF	1.0	3.4	5.0

To examine the relationships between the five contextual factors and generative AI use, we test for significant bi-directional Spearman correlations between these variables. The results are shown in Table 6. The correlation analysis between social support for AI use by the educational institution (SOE) and generative AI use shows significant, and in most cases highly significant, positive correlations for all 31 types of generative AI use. The strongest and highly significant correlations are between improving the language of one's own texts, writing texts, writing texts for blogs and forums, revising the content of one's own texts, answering teachers' questions, and researching sources (Table 6).

For the contextual variable of social support for AI use provided by parents (SOP), there are even slightly stronger correlations with students' generative AI use. The strongest correlations, with values greater than .40, are seen between SOP and use for writing texts, giving feedback on someone else's solution, writing texts for blogs or forums, checking the spelling of my own texts and revising the content of my own texts, answering questions from teachers, writing a blog, creating a social media post, improving the language of my texts, and creating tables, charts, or figures.

The analysis for the contextual factor parents' school leaving certificate (PAS) shows that in our data sample there are some negative correlations with students' use of generative AI. The use of generative AI for chatting, programming, giving feedback on someone else's solution, getting feedback on my own solution, writing texts for blogs and forums, writing a blog, writing a post, creating a social media post, improving the language of my own texts, researching sources, questioning texts and creating tables, charts or figures is significantly negatively correlated with PAS.

Table 6: Correlation between contextual factors and generative AI usage

Ways of generative AI use	**Contextual factors**				
	SOE	SOP	PAS	PAP	PAF
Doing homework	.34**	.39**	-.07	-.06	.05
Writing texts	.38**	.41**	.03	-.01	.09
Creating a text quickly	.31**	.37**	-.03	-.02	.14
Translating	.21**	.24**	.02	-.05	-.08
Playing games	.21**	.39**	-.06	-.05	.01
Chatting	.34**	.32**	-.24**	-.22**	-.06
Programming	.29**	.38**	-.26**	-.24**	-.03
Giving feedback on someone else's solution	.36**	.44**	-.24**	-.16*	-.09
Getting feedback on my own solution	.29**	.34**	-.19*	-.14	.04
Supporting brainstorming	.31**	.33**	-.08	.04	.12
Writing texts for blogs or forums	.37**	.49**	-.25**	-.18*	-.07
Checking the spelling of my texts	.32**	.43**	-.05	-.04	.02
Revising the content of my texts	.37**	.44**	-.10	-.17*	-.03
Performing research	.27**	.33**	-.08	-.05	.04
Answering questions from teachers	.37**	.42**	-.11	-.07	.02
Writing a blog	.33**	.41**	-.29**	-.18*	-.13
Writing a post	.35**	.38**	-.25**	-.18*	-.14
Correcting an e-mail	.28**	.35**	-.07	-.05	.03
Creating an outline for a text	.26**	.38**	-.14	-.07	-.09
Completing sentences	.26**	.37**	-.13	-.09	-.13
Creating lyrics	.25**	.39**	-.12	-.09	-.05
Solving math exercises	.22**	.34**	-.11	-.04	.01
Creating a social media post	.31**	.44**	-.25**	-.20*	-.08
Improving the language of my texts	.42**	.43**	-.16*	-.15*	.02
Researching sources	.37**	.37**	-.16*	-.18*	-.03
Finding literature	.35**	.28**	-.13	-.10	-.09
Questioning texts	.30**	.32**	-.17*	-.14	-.06
Getting inspiration	.30**	.24**	-.06	.04	.05
Getting advice	.28**	.38**	-.11	-.08	-.03
Chatting with literary characters	.29**	.36**	-.09	-.10	-.07
Creating tables, charts or figures	.26**	.41**	-.17*	-.13	-.07

*: significance of bidirectional correlation $p < 0.05$

**: significance of bidirectional correlation $p < 0.001$

SOE = social support provided by the educational institution; SOP = social support provided by parents; PAS = parents' school leaving level; PAP = parents' professional level; PAF = parents' financial situation

The analysis of the correlation between parents' professional qualification (PAP) and students' generative AI use shows some similarities when compared to parents' school education (PAS). There are some types of AI use that are not correlated with PAP but with PAS and vice versa. In addition, for PAS the correlation values are slightly greater and more significant for some AI usage ways such as for example for writing texts for blogs and forums or creating a social media post.

Finally, there are no significant correlations between the financial situation of the parents (PAF) and the use of generative AI. Compared to the other variables we considered as indicators of social status, PAS and PAP, the relationship between PAF and the use of generative AI does not seem to be relevant within our sample.

The results in Table 6 show that especially social support from both schools and parents can be considered of high importance for the use of generative AI. The results based on our sample also show that social status can also play an important role for or during the use of generative AI. However, the relationships between parents' social status and the different ways of using generative AI seem to be much more fragmented, and in particular the financial situation of parents seems to be less important.

4.4 Relationship between generative AI usage and students' self-perceived learning success (RQ4)

To answer research question 4, we compute the Spearman correlation coefficient between all 31 types of generative AI use and students' self-perceived AI-related learning success on a subsample of N = 111. The reason for performing the calculation on a subsample is that the learning success items were added during data collection based on feedback and discussions with experts in the field. The scale reliability of students' self-perceived AI-related learning success (LS) has a value of Cronbach's alpha = .912.

Table 7: Correlation coefficients between generative AI usage and self-perceived AI-related learning success (LS)

Ways of generative AI use		**Ways of generative AI use**	
Doing homework	.74**	*Writing a post*	.19
Writing texts	.69**	*Correcting an e-mail*	.26**
Creating a text quickly	.76**	*Creating an outline for a text*	.55**
Translating	.24**	*Completing sentences*	.31**
Playing games	.12	*Creating lyrics*	.23**
Chatting	.22*	*Solving math exercises*	.46**
Programming	.29**	*Creating a social media post*	.23**
Giving feedback on someone else's solution	.43**	*Improving the language of my own texts*	.57**
Getting feedback on my own solution	.44**	*Researching sources*	.39**
Supporting brainstorming	.58**	*Finding literature*	.24*
Writing texts for blogs or forums	.42**	*Questioning texts*	.45**
Checking the spelling of my own texts	.33**	*Getting inspiration*	.48**
Revising the content of my own texts	.58**	*Getting advice*	.40**
Performing research	.63**	*Chatting with literary characters or historical persons*	.33**
Answering questions from teachers	.51**	*Creating tables, charts or graphical elements*	.47**
Writing a blog	.29**		

*: significance of bidirectional correlation $p < 0.05$
**: significance of bidirectional correlation $p < 0.001$

From the results in Table 7, it can be concluded that students' self-perceived learning success is significantly positively correlated with 29 out of 31 items of generative AI usage frequency. For nine of the types of generative AI use, namely doing homework, writing texts, creating a text quickly, supporting brainstorming, revising the content of my own text, doing research, answering teachers' questions, creating an outline for a text, and improving the language of my own texts, the correlation coefficients are even greater than .50. The correlation coefficients for doing homework and creating a text quickly are even higher than .70. Thus, the perception of being successful in school with the help of AI seems to be highly positively related to the actual use of generative AI. It is also worth noting that the tasks that are highly correlated with self-perceived AI-related learning success are tasks that are clearly related to school.

4.5 Grouping of generative AI usage into higher order concepts (RQ5)

To answer RQ5, we perform an exploratory factor analysis (EFA) on the 31 items. First, we test whether our data are suitable for conducting an EFA using the Bartlett's test for sphericity and the Kaiser-Meyer-Olkin (KMO) measure (Fabrigar and Wegener, 2011). The Bartlett's test tests the null hypothesis that the correlation matrix of items is an identity matrix to ensure that there are some relationships between items or groups of items. Therefore, Bartlett's test should be significant. The Kaiser-Meyer-Olkin measure is a measure of the proportion of variance among items that may be shared in the variance. KMO values between 0.8 and 1 indicate that the sample is adequate for EFA. In our case, the Bartlett's test is significant with $Chi^2(300)=2468.09$ and $p < 0.001$ and the KMO value is .915. Since both tests indicate that the sample is adequate for EFA, we proceed with the analysis.

We perform a varimax rotation and use a weighted least squares (WLS) estimator. Only items that are significantly correlated with at least two other items and have factor loadings greater than 0.33 are included in the analysis. Thus, we include in the analysis the items with the numbers 1, 2, 3, 5, 6, 9, 10, 11, 12, 13, 16, 17, 20, 21, 23, 28, 29.

Table 8: Groups of generative AI usage

Items and factors		**Factor loadings per factor 1 to 4**			
		1	**2**	**3**	**4**
Factor 1: performing standard tasks					
1	Doing homework	.681			
2	Writing texts	.906			
3	Creating texts quickly	.746			
Factor 2: exploring new opportunities					
5	Chatting		.551		
6	Playing		.686		
11	Creating texts for blogs and forums		.681		
16	Creating blogs		.832		
17	Creating posts		.942		
20	Completing sentences		.607		
21	Creating lyrics		.773		
23	Creating social media post		.839		
Factor 3: improving one's own work results					
9	Getting feedback on your own solution			.639	
12	Checking the spelling of your own text			.706	
13	Revising the content of your own text			.709	
Factor 4: inspiring creative thinking					
10	Supporting brain storming				.644
28	Using as a source of inspiration				.614
29	Using as an advisor				.571
Percentage of Variance explained (sum: 67.7 %)		**15.03%**	**29.68%**	**12,14%**	**10.83%**
Cronbach's alpha		**.890**	**.927**	**.849**	**.808**

The final result of the EFA (see Table 8) consists of the four factors we named "performing standard tasks", "exploring new opportunities", "improving one's own work results", and "inspiring creative thinking". The total variance explained is 67.7%. Table 8 shows, based on the statistical analysis, how the 31 ways of using generative AI can be grouped into each of the four higher-order concepts and factors. These results can illustrate, for example, that if a student uses generative AI to do homework, the same person may also use it more likely to write texts and to create texts quickly. As a result, the four higher-order concepts of generative AI use can be interpreted as an initial consolidation of generative AI use in four complementary areas and can help to better understand students' routines of generative AI use and how to support them.

5. Discussion and recommendations

In the present work, we conducted a quantitative study on a dataset collected between March and July 2023 from 15-19 year old students. The aim of the study was to investigate whether, for which tasks, and how often students use generative AI in or for school. In addition, we examined whether and what kind of relationships exist between the intensity of students' use of generative AI and individual action-guiding characteristics considered crucial for technology use, such as social perception of AI, need for cognition, AI-related self-efficacy expectations, technostress, and readiness to use technology. We also analyzed how contextual factors, such as social support for AI use from schools and parents, and the social status of students' parents, are related to students' AI use intensity. In addition, we examined whether there is a relationship between students' AI use intensity and their perceived AI-related learning success, and whether the 31 generative AI uses can be grouped into higher-order concepts.

The results of our sample show that 50% to 80% of the responding students never use generative AI for many of the given uses. This could be due to the fact that generative AI is still a very new tool and should be set in relation to many other learning tools and methods already used in school. However, based on our findings, we argue that the use of this novel technology in or for school is becoming increasingly important, especially for specific school-related tasks such as doing homework, writing, rapid text generation, translation, and brainstorming or research support.

Regarding the use of generative AI and the set of students' action-guiding characteristics, we found some significant relationships with different ways of using generative AI. One very interesting aspect, for example, is that the perception of generative AI as human-like, e.g. as "warm", "organic" or "real", might play an important role for the use of such technologies, since for most types of use we found a significant positive correlation with students' perception of the AI as anthropomorphic. We also found significant positive correlations between perceived AI-related self-efficacy expectation and generative AI use intensity for most of the 31 generative AI use types. This may mean that AI-related self-efficacy expectation can be assumed to be crucial when using generative AI in or for school. In addition, there are significant positive correlations between students' self-perceived technostress and generative AI use. This finding is in line with current research (Ragu-Nathan et al., 2008; Tarafdar et al., 2011). However, in our data, the correlation values are moderate for most of the usage types. Interestingly, students seem to be most stressed when they are simultaneously using AI to write a blog or post, or to create a social media post. For these items, the correlation values are greater than .40 and highly significant. In particular, the students rate their skills to be lower than the demands resulting of using the technology. It can be assumed that the students feel to be not productive or experienced enough with this kind of digital tools.

Furthermore, students' need for cognition, a concept that indicates cognitive engagement or general enjoyment in thinking, is negatively correlated with a number of different uses of generative AI, such as solving math problems or answering teachers' questions. One could infer that more frequent use of AI may be associated with a decrease in cognitive engagement and enjoyment. This could be interpreted as a concern for the future, as the availability and intensity of use of AI-based generators is expected to increase. A particular challenge and at the same time an opportunity that can arise from these results is that the education system in Germany should more focus on the sustainable development of students' key competencies such as critical thinking, self-reflection, improvisation or creativity. In our opinion, more innovative solutions for future-oriented educational approaches have to be developed.

Another aspect we find important is that there are positive correlations between students' technology acceptance convictions and different ways of using AI, but for technology competence convictions there are many highly significant negative correlations. Technology acceptance tends to focus on the development of an intention to use a technology based on ease of use and usefulness, while technology competence conviction represents an individual's subjective expectation of possible courses of action in technology-related situations (see Neyer et al., 2016, p. 88). The latter has a more explicit orientation towards students' cognitive processes about how and for what purpose generative AI could be used in particular, e.g., to achieve individual goals. We argue that the reason for this finding may be that students are still not fully aware of the ever-increasing possibilities and possible actions and interactions that generative AI tools can offer to them, on the one hand, and are still critical regarding this new and perhaps unfamiliar technology, on the other hand.

The analysis of the role of contextual factors in the use of generative AI revealed that social support from parents and educational institutions, as well as parents' social status, may play a significant role for the ways students use generative AI. In particular, social support from both schools and parents can be considered of high importance for or during generative AI use. This may mean that students demand a certain level of empowerment for the use of generative AI, which is seen as indirect support from parents or teachers, e.g. the availability of generative AI by providing access to this technology. At the same time, students may also demand more direct support for the use of generative AI, such as shared critical reflection on the opportunities but also the risks of generative AI. From our perspective, much more research is needed in the area of social support to be more specific about direct and indirect interventions by parents and teachers. In addition, the data also show that social status may play an important role for or during the use of generative AI. However, the relationships between social status and the different ways of using generative AI seem to be rather fragmented, and in particular the financial situation of parents seems to be less important. Nevertheless, we suggest that the role of students' parents' educational and financial situation should not be underestimated in terms of educational equity. We argue that this new technology can be both a new driver for more educational equity in Germany and a new risk for ever-growing inequality in our educational system, e.g. in cases where widespread access to generative AI for students is not accompanied by elements of direct and indirect support and joint discourse as mentioned above.

Regarding a consolidation of the whole list of 31 ways of using generative AI into higher-order concepts, based on our statistical findings, the considered ways of using generative AI can be grouped into four dimensions. Based on the compositions of the respective factors, we propose to name these dimensions *performing standard tasks, exploring new possibilities, improving one's own work results*, and *inspiring creative thinking*. We anticipate that these groups don't represent a final concept yet, in particular due to the expected further expansion of generative AI capabilities, general technological developments, as well as changes in the creativity of students and other user groups. Rather, the list can be seen as a first suggestion or a starting point for further empirical research and statistical analysis.

Finally, the study showed that students' self-perceived and AI-related learning success is significantly positively correlated with almost all types of generative AI use. We find it noteworthy that for generative AI uses such as writing texts, supporting brainstorming, revising the content of my own text, conducting research, answering teachers' questions, creating an outline for a text, as well as improving the language of my own text, the correlation coefficient is even higher than .50, while the correlation coefficients between AI-related learning success and doing homework and creating a text quickly are even higher than .70. At the same time, the use for playing games is not significantly correlated with students' self-perceived learning success. We are fully aware that the present sample is not representative. However, the study provides initial evidence that students today, and most likely to a greater extent in the future, may be highly engaged with generative AI as an always-available and very helpful intelligent assistant. On the other hand, we see the risk that students may assume that their individual learning outcomes, which in schools are traditionally represented by adequate grades, could be optimized by some kind of flat-rate use of generative AI. In our view, this tension creates a completely new dynamic in the context of modern education and may increase the pressure to orient the education system even more quickly and explicitly towards a competence-oriented approach instead of the qualification-oriented logic of the past. In general, we argue that questions of how to assess, recognize and value students' individual learning progress, competence and personality development in a fair and transparent way cannot be answered by the same approaches that were applied before generative AI came into play. Of course, these kinds of questions are not new, but the answers are changing completely due to the new dynamics created by generative AI. From our point of view, these kinds of AI-based technologies can be seen as a strong booster for innovative solutions towards a more competency-oriented education system of the future, in Germany and beyond.

This study as such, including the analysis and the reported results, is one of the very few empirical investigations among teen-aged students and their self-reported information about the usage of generative AI. We would like to invite researchers, education experts, policy makers, and practitioners to understand this work as a starting point for exploring the current and future dynamics around generative AI in education. From our perspective the main contribution of this study is the provision of initial evidence for various assumptions and initiatives that are currently being discussed in educational practice and research. More empirical research is needed in this area, especially longitudinal studies, to better understand the actual causes and effects, e.g. of different ways of using generative AI, the resulting outcomes such as actual learning success, and a critical reflection on how to evaluate, recognize, and appreciate students' actual competence gains in education. We invite all those interested in this field to participate in further empirical studies or investigations and to engage in joint discussions. With our research we aim to support the continuous development of a future-oriented education system in Germany and beyond.

6. Limitations

Regarding the results of the factor analysis, further critical reflection and empirical investigation on a more representative sample with more data points as well as a confirmatory factor analysis are crucial for a meaningful structure and naming of the four factors of consolidated generative AI use revealed. Further discussions with experts in the field could be very helpful. The technology commitment scale used in this study has not yet been tested with students. However, the reliabilities of the scale showed good results, so we decided to use it for our analysis, as it offers an interesting extension to the classical technology acceptance model. Furthermore, as this study is based on correlational analysis with only one measurement point, it is important to mention that the correlations should not be interpreted in a way that there are causal relationships between the measured variables.

Our sample structure shows a relatively high proportion of students (49%) who live in a more academically oriented family context, which is higher than the average for families in Germany. In addition, the financial situation of about 45% of the students in our sample was judged to be above average. One reason for these results can be seen in the fact that three of the four schools from which the students in our sample come are high schools (Gymnasien). These aspects and the fact that the sample size is still limited indicate that our study is not yet representative. Furthermore, this data is based solely on the students' self-assessment. Nevertheless, it is one of the first studies to consider the actual perspectives of students at school on how they use generative AI for different tasks. From our point of view, further empirical research and especially longitudinal studies are very important to better understand how generative AI affects learning processes in educational institutions and how educational systems can be transformed.

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