

Exploring the Student Perspective: Assessing Technology Readiness and Acceptance for Adopting Large Language Models in Higher Education

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Abstract: Digital technologies are changing and will continue to change how we learn and teach today and in the future. With the latest developments in the field of generative artificial intelligence (AI), particularly large language models (LLMs), the question of using AI-based tools in academic education is ruling the current discussions about the transformative impact of AI in higher education (HE).

These discussions range from banning these technologies for learning and teaching in HE to guided study support. This study avoids taking up these multifarious and partly controversial debates. Instead, we show how students perceive using AI-based tools for automated text generation for their studies. Drawing on a synthesis of two theories: the 'Technology Readiness Index' (TRI) and 'Technology Acceptance Model' (TAM). The model is validated based on survey data collected among undergraduate first-semester students ($N=111$) of a computer science-related study programme in Germany in winter 2022/23. The students had to evaluate their relationship to that new technology focusing on their readiness for technology adoption and acceptance. By analysing the collected data with a partial least squares model, we find that the optimism toward the new technology positively influences technology acceptance, while discomfort with the technology negatively influences perceived ease of use. The paper concludes with recommendations for action for adopting LLMs in HE. A proper investment in building AI skills in academic teaching plays a valuable role in fostering the students' positive attitude and innovativeness towards this new technology. Additionally, there is a need for more education about the risks and challenges of using this technology to reduce the impact of factors such as discomfort on ease of use. This requires a factual discourse, away from the current hype-induced exaggerated and hyperbolic statements, for instance, in developing formal guidance for universities.

Keywords: Student Perspective, Technology Readiness, Technology Acceptance, Large Language Models, Higher Education

1. Introduction

Recent breakthroughs in generative artificial intelligence (AI) have massively influenced the current AI hype and the discussions about the impact of such a transformative digital technology like AI. Generative AI is an umbrella term for general-purpose systems based on machine learning (ML) and natural language processing (NLP) for creating new content, including text, audio, video, software code or simulations. Such systems use vast amounts of data to train their deep neural networks and conceptualise patterns of multimedia-related new content based on their probabilistic nature, like art, images, movies, music, texts or software programs. A powerful representative of these AI systems is the Large Language Models (LLMs). These systems represent "generative mathematical models of statistical distribution of tokens" (Shanahan, 2022, p. 2) as universal language processing tools. These pre-trained models are parameterised by a neural network that gets their training data from the massive amount of publicly available human-generated text. With their ability to provide a probabilistic distribution of word sequences, they are modelling natural language texts based on statistics, information theory, and machine learning (Li, 2022). This transformation process demonstrates the current potential of large language models, which empower humans to ask the system questions in natural language (called prompts) and receive answers. LLMs are a new technology, especially their usage in (higher) education for teachers and learners. Even though tools already exist to support the writing process, this kind of technology, which might take over the entire creative writing process, is entirely new and unique. This kind of interaction with the system leads us to believe that these systems are intelligent and that the results are justifiable. An important debate about the results' trustworthiness, credibility and comprehensibility of generative AI is ongoing. It requires close attention and further research, not only in the (higher) education field (Crawford, Cowling and Allen, 2023; Bender et al, 2021; Weidinger et al, 2021).

Our paper sets a different focus by investigating how students perceive this new technology, what behaviour and what relationship they develop with this technology by measuring their readiness and acceptance. The long-established theories of TRI and TAM in information systems research (see Venkatesh, Davis and Moris, 2007) are particularly well suited for this investigation and are applied as a combined model for the first time in the context of LLMs. This paper contributes to making the current debate on the use of LLMs in HE more objective. In particular, we examine students' willingness to use these technologies by surveying 111 first-year undergraduate students in a German Higher Education Institution (HE). The students' perception of LLMs for their daily study work might shape future action plans for handling the use of LLMs in HE.

2. Related Work

The current hype around the potential uses of LLMs in HE has led to increased research. Kasneci et al (2023) or Gimpel et al (2023) investigate the opportunities and challenges of LLMs for HE from a teacher's and student's perspectives. Farrokhnia et al (2023) or Su and Yang (2023) combine general aspects of generative AI with a close focus on ChatGPT (a specific LLM product) and its adoption in HE. Lim et al (2023) demand attention to the paradoxes of generative AI and provide implications for the future of education from the perspective of management educators. Other work is devoted to specific aspects of generative AI in HE, such as Rudolph, Tan and Tan (2023) or Savelka et al (2023) about assessments in HE. Further work, such as Chan and Hu (2023) or Sullivan, Kelly and McLaughlan (2023), look mainly at the impact of using LLMs from the student's perspective.

Most papers show that generative AI in HE is an emerging technology, especially LLMs, with a broad scope of new applications but also risks and limitations for students and lecturers, which needs further investigation. Our paper answers this need by examining how students are prepared to anticipate this new technology based on a quantitative survey. We know from information systems research that the user's willingness to interact with a new technology influences the possibilities of technology adoption in an organisational setting. Therefore, our paper focusses on the students' behaviour, intentions, and treatment of this new technology. For this purpose, we apply the theory of Technology Readiness Index (TRI) and combine it with the Technology Acceptance Model (TAM). These two theories stand as research paradigms to explain technology adoption and acceptance, according to Porter and Donthu (2006).

While TAM predicts individual adoption and use of new technology (Venkatesh and Bala, 2008), TRI focuses on the measurement of technology readiness as "people's propensity to embrace and use new technologies for accomplishing goals in home life and work" (Parasuraman and Colby, 2015). These theories were initially developed separately and used insights from psychology (Levina, 2021) and marketing research (Parasuraman, 2000). Other works like Lin et al (2005), Lin, Shih and Sher (2007), Walczuch, Lemmink and Streukens (2007) or Godoe and Johanson (2012), Koivisto (2016) and Gao et al (2022) show how these two theories can be combined. Thus, the factors influencing the readiness positively and negatively, according to TRI, compose the exogenous variables that determine the perceived usefulness and ease of use of new technology in terms of TAM. We will call such an integrated framework TRI-TAM.

Current work that deals with the readiness of AI-based systems uses the findings from TRI combined with other approaches, especially from 'customer experience' research (Alami et al, 2021 or Gao et al, 2022) or only focusing on the investigation of technology acceptance and user experience (Mlekus, 2020). However, we see an advantage in applying an integrated model that measures the readiness of users and their influence on the acceptance of these new AI-based LLMs. Moreover, past research shows the usefulness of this integrated model. Therefore, we apply this approach as a theoretical framework for our study, specifically for the new technology of LLMs in HE.

3. Theoretical Framework and Hypotheses Development

The technology readiness for new technology is represented by positive and negative factors influencing the user's willingness to interact with this new technology. According to Parasuraman (2000) and Parasuraman and Colby (2001, 2015), optimism and innovativeness are *contributors* that increase an individual's readiness, while discomfort and insecurity as *inhibitors* show adverse effects on readiness. With a 36-item scale, TRI measures "people's propensity to embrace and use new technology for accomplishing goals in home life and at work" (Parasuraman 2000, p. 308).

TAM investigates how a technology's attributes affect an individual's perception of technology (Porter and Donthu, 2006). These two primary *predictors* are perceived usefulness (PU) and perceived ease of use (PEOU)

(Davis, 1989). According to Davis (1989, p. 320), PU is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance”, while PEOU “refers to the degree to which a person believes that using a particular system would be free of effort”. Davis, Bagozzi and Warshaw (1989) show in the original TAM versions 1 and 2 the influence that PU and PEOU have on behavioural intentions, which affect the actual use of new technology. The different applications of the TRI-TAM framework recap this two-stage influence of technology acceptance to only one factor, mostly called actual use or use intention.

According to the different approaches of TRI-TAM, our research study will investigate only one contributor and one inhibitor factor and their effects of PU and PEOU in terms of LLM adoption in HE. Here, optimism is defined as a positive view of new technology, while innovativeness primarily expresses the tendency to be able to take on a pioneering role with the application of the technology. In contrast, discomfort expresses a perceived lack of control over technology, and insecurity encompasses distrust of technology. (Parasuraman and Colby, 2001).

Initial study results on LLM adoption in HE show some main positive aspects: the personalisation of learning or adaptive learning (Zhai, 2022; Su and Yang, 2023; Kasneci et al, 2023), the direct support of the writing process (Wessels, 2022; Kasneci et al, 2023), dissolving writer’s blocks (Wessels, 2022) or improving critical thinking and problem-solving (Kasneci, 2023). Furthermore, LLMs can work as tutors and mentors, analyse the learning process, identify specific learning or educational needs early on (Zhai, 2022; Kasneci et al, 2023), and making work (Su and Yang, 2023). In contrast, the positive aspects of being innovative and taking on a pioneering role with the use of such systems was hardly mentioned as a reason. Positive technology readiness refers to optimism or to students’ hope and confidence that LLMs will improve their study work. The optimistic motives predominate the positive factors and therefore we subordinate the aspects of innovativeness to one positive factor and name it *Optimism (OP)*.

The negative factors of TRI reinforce the user's tendency to avoid adopting this new technology. Here, previous studies argue mainly from an ethical point of view (Tuomi, 2023; Weidinger et al, 2021) and discuss systems based on the functionality of ML and NLP (Chatterjee and Dethlefs, 2023). These include, for example, concerns about the originality and plagiarism of academic work using LLM or, more generally, the dangers of AI-assisted cheating (Lim et al, 2023; Milano, McGrane and Leonelli, 2023). The lack of trustworthiness in these systems is not a major issue that negatively influences the perceived usefulness and ease of use of LLMs, which might be due to the current hype around these systems (Hu, 2023). For these reasons, we combine insecurity and discomfort as an inhibitor for readiness and define only one TRI-related negative factor *Discomfort (DI)*.

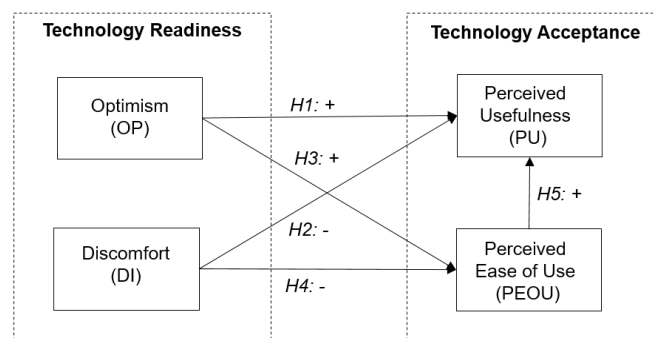


Figure 1: The integrated TRI-TAM framework for LLMs in HE (according to Lin et al. 2007; Godeo and Johanson 2012; Gao et al. 2022)

The TRI-TAM literature defines TRI-related factors as exogenous variables influencing technology acceptance (Lin et al, 2005; Godoe and Johanson, 2012). In our case, optimism and discomfort are the two exogenous variables that affect the perceived usefulness and ease of use of LLM adoption in HE. In particular, Gao et al (2022); their study of another AI-based new technology argues that a positive attitude towards this technology reinforces how, with what intensity and with what success it is used. On the other hand, a negative effect causes the user to feel overwhelmed by the technology because it seems too complicated and complex. The behaviour in the use of this technology is thus negatively influenced. Thus, according to these arguments, the strength of technology acceptance depends essentially on a positively PU and PEOU. In addition, PU is further enhanced by the effects of a PEOU. Previous findings from TAM (Davis, 1989; Venkatesh and Bala, 2008) show that PU represents the degree of AU, more so than PEOU. While PEOU tends to reflect experience and voluntariness, PU tends to show up in factors such as subjective norms, job relevance, or output quality (Venkatesh and Bala,

2008). Our theoretical TRI-TAM framework contains two TRI-related factors, one positive, one negative, which differently influence the technology acceptance typified as PU and PEOU with the corresponding hypotheses (see figure 2 in section 5). Based on the above-discussed literature, we pose the following five hypotheses to investigate the student’s readiness and acceptance of LLMs in HE (see figure 1):

- H1. Optimism (OP) has a positive impact on perceived usefulness (PU).
- H2. Discomfort (DI) has a negative impact on perceived usefulness (PU).
- H3. Optimism (OP) has a positive impact on perceived ease of use (PEOU).
- H4: Discomfort (DI) has a negative impact on perceived ease of use (PEOU).
- H5: Perceived ease of use (PEOU) is positively related to perceived usefulness (PU).

4. Data and methodology

The entire study embodied two phases. In the first phase, to get familiar with the tools, the students were asked to use LLMs to generate three different texts. In the second phase, which took place from the end of December 2022 to the beginning of January 2023 and is the focus of this paper, each student must complete a questionnaire. The survey consisted of 45 items taken from the TRI and TAM literature. The items and their structure closely follow the study design of the Godoe and Johanson (2012) survey and are based on the original frameworks by Parasuraman (2000) and Davis (1989). Our questionnaire contains 31 technology belief statements, both positive and negative, related to our defined two readiness factors of OP and DI, our first two factors. The two other factors, PU and PEOU, with a total of twelve items, complement the questionnaire regarding technology acceptance. Each of the 45 items was measured either on a 5-point or a 7-point Likert-scale.

118 students from a bachelor’s programme in Business Information Systems at a German university of applied science were asked about their attitudes and views on using AI-based automated text generation tools. The entire student group consisted of 15.3% women and 84.7% men with an average age of 19.67 years. After cleaning the not fully answered surveys from the collected data set, a usable sample of $N=111$ was available. 77.8% of the students reported having no experience with LLMs prior to the study. They first came into contact with the tools through this study and thus used them for the first time. Only 22.8% had already had their first experience. At the time of data collection, all students used the GPT-3-based playground with a technical interface which allowed tuning the language modelling algorithm and its outputs. The GPT-3 model (Generated Pre-Trained Transformer 3), founded and operated by the US-American company OpenAI, was the best-known and most widely used model at the time of this study.

Constructs and items	Mean (Std Dev)	Factorial Loading	Cronbach's Alpha
Optimism (Technology Readiness)			
OP1 AI-based tools for automated text generation give you as a student more control over your studies.	3.03 (1.13)	0.721	0.808
OP2 AI-based tools for automated text generation are more convenient to use than traditional writing tools.	3.96 (1.04)	0.661	
OP3 You like AI-based tools for automated text generation that (partially) automate your student assignments because they give you more freedom.	3.54 (1.11)	0.818	
OP4 You prefer to implement the latest technologies for your student assignments.	4.04 (0.99)	0.475	
OP5 You like such tools that allow you to adapt your student assignments to your needs.	4.18 (0.87)	0.458	
OP6 AI-based tools for automated text generation make completing your student assignments more efficient.	3.74 (1.10)	0.799	
OP7 AI-based tools for automated text generation give you more freedom to concretely complete your student assignments.	3.32 (0.98)	0.617	
OP8 Learning the AI-based tools for automated text generation can be just as rewarding as the technology itself.	3.70 (1.07)	0.519	
OP9 You feel confident that AI-based tools for automated text generation will do what you have instructed them to do.	3.21 (1.05)	0.555	
Discomfort (Technology Readiness)			
DI1 Instruction manuals or help pages on AI-based tools are not helpful because things are not explained in a way that you understand.	2.24 (0.90)	0.670	0.638
DI2 Sometimes you get the impression that the latest tools and technologies are not designed for use by 'normal' people.	2.62 (1.09)	0.576	
DI3 There are fundamentally no explanations about the latest tools or technologies written in simple language.	2.50 (1.07)	0.821	
DI4 Sometimes when you get help with the explanation of AI-based tools, you feel like you're being exploited by someone who understands more than you.	1.83 (0.97)	0.600	
DI5 It is embarrassing when you have trouble using concrete AI-based tools while others are watching.	1.81 (1.07)	0.495	
Perceived Usefulness (Technology Acceptance)			
PU1 AI-based tools for automated text generation allow me to complete assignments more quickly.	5.40 (1.16)	0.818	0.882
PU2 Using AI-based tools for automated text generation improves my work performance.	4.72 (1.32)	0.792	
PU3 Using AI-based tools for automated text generation increases my productivity.	4.70 (1.60)	0.820	
PU4 Using AI-based tools for automated text generation facilitates the completion of my student assignments.	5.04 (1.41)	0.824	
PU5 Overall, I find AI-based automated text generation tools useful for completing my student assignments.	5.29 (1.41)	0.869	
Perceived Ease of Use (Technology Acceptance)			
PEOU1 I find it easy to get AI-based automated text generation tools to do what I want.	5.14 (1.15)	0.826	0.787
PEOU2 The use of AI-based tools for automated text generation is clear and understandable.	5.23 (1.15)	0.872	
PEOU3 It is easy for me to remember how to perform tasks with the AI-based tools for automated text generation.	4.95 (1.40)	0.580	
PEOU4 Overall, I find the AI-based tools for automated text generation easy to use.	5.39 (1.04)	0.839	

Figure 2: Selected items for the final TRI-TAM scale according to its Cronbach’s alpha of the TRI-TAM framework for LLMs in HE

5. Results and Discussion

Partial Least Squares (PLS) analysis was used to validate the measurement and structural properties of our theoretical research model. PLS was applied as it tests the properties of the measured items while also analysing the direction and strength of our hypotheses (Hair et al, 2022). The internal consistency was assessed through Cronbach's alpha (see figure 2), composite reliability and Average Variance Expected (AVE).

21 items were taken out because of low factor loadings. Only one Cronbach's alpha was between 0.6 and 0.7, all others had values above 0.7. The relatively high number of excluded items due to low Cronbach alpha's was a surprise as all questions were derived from verified scales. However, these scales were never used in connection to LLMs and we asked the questions to a relatively homogeneous group of survey participants.

The evaluation of the structural model (inner model) showed that all VIF values were below 3, so no collinearity issues could be found. The Standardized Root Mean Square Residual (SRMR) index of our model is below the recommended upper threshold of 0.1. The recommended criteria of 0.8 for the Normed Fit Index (NFI) has also been surpassed by our model. Results from the PLS analysis of the structural model, including path coefficients and their statistical significance, are illustrated in figure 3. Standard errors were computed by a bootstrapping procedure with 500 re-samples. Our analysis substantiated the hypothesised relationships H1, H3 and H4 by empirical evidence. OO has a positive and significant effect on PU ($\beta = 0.755$; $p \leq 0.001$) and PEOU ($\beta = 0.337$, $p \leq 0.001$). Furthermore, DI negatively and significantly influences PEOU ($\beta = -0.271$, $p \leq 0.001$). However, DI does not significantly influence PU, and PEOU does not significantly influence PU, so the hypotheses H2 and H5 do not hold as figure 3 shows.

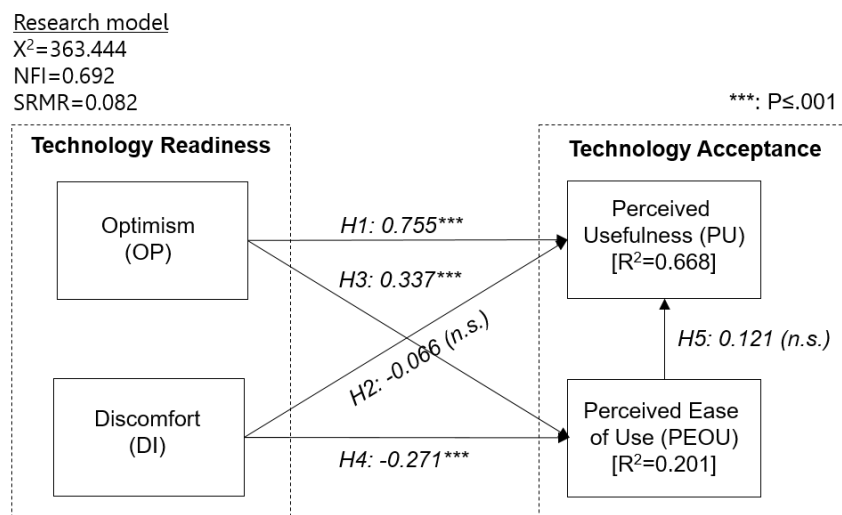


Figure 3: Research Model of TRI-TAM framework for LLMs in HE [sample $N=111$]

5.1 Optimism and perceived use and perceived ease of use

The results from our study confirm the hypotheses that optimism positively influences PU and PEOU. Several studies (Lin et al 2005, Godeo and Johanson, 2012) have already demonstrated this connection in examining various technologies that were new at that time.

The examination of the reliability and validity of the data also showed a high Cronbach's alpha (0.808) for the factor OP, so that only those items with a low factor loading were removed. These items were mainly related to statements addressing motives of innovativeness. We suspect that the homogeneity of the student group with a similar age and an assumed high affinity for technology through the field of study does not consider a pioneering role relevant compared with the group's peers. Students prefer using these tools if it simplifies their daily study routine, helps them to fulfil their writing tasks, and thus makes them more efficient. Consequently, these motives strongly impact the perceived usefulness of the tools more than the perceived ease of use. These insights also align with previous research findings (Gimpel et al, 2023; Sullivan, Kelly and McLaughlan, 2023) on the impact of LLMs in HE.

5.2 Discomfort and perceived use and perceived ease of use

Interpreting the results regarding the inhibitor factor of DI and its influence on PU and PEOU is more complicated. In particular, it was necessary to remove items that contained statements about the distrust or dangers of such tools. The students' answers were too homogeneous (very high or very low mean). Contrary to our expectations, the test of our hypothesis did not reveal a strong negative influence of Discomfort on PU and PEOU. We only find a moderately negative relationship of DI and PEOU, although we also hypothesised a negative influence of DI on PU. This is in line with, for example, the findings of Godeo and Johanson (2012, p 41), who argued that discomfort does not have a negative impact on PU because users "see the main value of a system, regardless of how they handle it". We hypothesised negative impact on PU against the backdrop of excessive media attention on LLMs, especially ChatGPT, at the time of conducting the survey. On the one hand, the students used the technical interface of the GPT-3 playground model that helped them to influence the underlying algorithms and understand partly how they are working. On the other hand, when they had to answer the survey, the user-friendly interface for ChatGPT had just launched, causing the hype around LLMs, also in the education field. In particular, the debate about the dangers, risks and the first bans at universities or even countries might have negatively influenced the students. The results of the survey do not confirm this assumption. The students did not so much see the dangers or distrust the new technology, but motives such as the concrete functioning or handling of the tool played a determining role in answering the items. Interestingly, the students answered statements about the dangers or risks of these tools or the possibilities of being used by governments or states for manipulation without impacting their PU. These items also showed low factor loadings and were therefore removed. Thus, the assumption we made earlier that the students would be negatively influenced by adverse reporting and therefore assess the usefulness of such tools differently did not apply.

5.3 Perceived ease of use and perceived usefulness

Prior studies argue that perceived ease of use contributes to perceived usefulness (Godeo and Johanson, 2012; Lin et al 2005). We also followed this assumption but couldn't confirm this hypothesis here. It is, above all, the overwhelming simplicity of using these tools that others also see as an argument for their widespread everyday use (Milano, McGrane and Leonelli, 2023; Gimbel et al, 2023). While in past technology adoption there was often a gap between the usefulness of a tool and its ease of use, it is precisely these new tools of the digital age that are enormously easy to use.

6. Conclusion

6.1 Recommendations for Action

LLMs are regarded as a learning tool from the students' perspective, serving as aids in simplifying their everyday studies. This should be taken seriously by HE (UNESCO, 2023). In particular, the tools should be integrated into everyday teaching, given that students already exhibit high technology readiness and acceptance to use them. It also means that academic writing skills must be integrated into all teaching areas, for example, as a tool to strengthen critical thinking (Milano, McGrane and Leonelli, 2023). Overall, HE teachers should focus on enabling specific AI skills so that students can evaluate the output of the tools. They should be better able to assess the limitations and risks of these tools - as our study showed that students still need more awareness - and they should better understand how these tools work. The origin of the results should become the focus of a more substantial examination of these tools.

On the one hand, students need to understand that these systems mainly use freely accessible internet sources as data for their pre-training (Kasneci et al, 2023). Therefore, the prompt results may lack accuracy in areas with necessary specific expertise or may verge into plagiarism (Lucchi, 2023). On the other hand, these tools tend to generate speculative content (Bang et al, 2023), emphasizing the urgency to train students to check the correctness of content for meaningful everyday pedagogical practice. Additionally, LLMs have several potential ethical violations like threats to privacy and security, and consequences of biases (Dwivedi et al, 2023) and discrimination, that students should be more aware of when using these tools. The positive attitudes to using these tools are also increasingly reflected in the fact that students use them more and more for examinations, especially for writing academic papers. Here, teachers and HEs are challenged to rethink the existing structures and paradigms of exams in academia and look for new innovative evaluation methodologies. All in all, it requires guidelines for using these tools so that the perceived positive attitude of the students leads to the reinforcement

of individual and collective learning success (Dwivedi et al, 2023). These guidelines should also clarify the directives from the teachers' point of view and thus represent a fundamental new institutional document in HE.

6.2 Future Research

Further research should focus on some different facets. First, the teachers' perspective should also be examined. A comparative study could investigate the extent to which teachers are prepared to adapt to this new technology and the factors underpinning their readiness and acceptability. Second, while our study specifically collected data from information systems students with an inherent curiosity for new technologies, future work could encompass a more diverse spectrum of students, including other study subjects like social sciences. This would enrich the dataset and facilitate the control of demographic influences. Furthermore, we collected data during the first launch of Large Language Models, where the general risks of these models were not yet seriously discussed. Future studies should examine the associated ethical challenges and risks more closely.

Overall, the acceptance measurement of new technology adoption also shows comparable patterns to numerous past studies, e.g. Saber and Souiden (2010), Koivisto et al (2016), and Gao et al (2022). Optimism (and innovativeness in general) promote a positive attitude towards new technology. At the same time, discomfort and uncertainty weaken this attitude and thus influence the usability of new technology and the awareness of ease of use. Third, this study shows two significant changes requiring further and more extensive investigation, especially in further developing TRI and TAM theories alongside their associated measurement scales. On the one hand, the fundamental change in technology use has changed behaviour and attitudes towards new technologies. Today, ubiquity and omnipresence touch all areas of life and work and thus demand new ways of human interaction with new technologies, which generally create a higher level of technology acceptance to deal with new technologies. On the other hand, the user-friendliness or usability of modern technologies has also increased highly, so people are more open to using new technologies. These changes can impact how users perceive new technologies. These transformative dynamics necessitate reconsidering how users perceive and evaluate new technologies, thereby mandating a fundamental reevaluation of the underlying measurement scale structure.

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