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Articles

Students' wishes for digital higher education: preferences in and expected added value of future learning formats

Studierendenwünsche an digitale Hochschullehre: Präferenzen für und erwarteter Mehrwert von zukünftigen Lernformaten

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Abstract

Digital learning formats have the potential to enhance higher education. Implementation of formats utilizing extended reality, gaming, and artificial intelligence in future teaching should be guided not only by technical possibilities but also by students' preferences and evaluations. Computer science and engineering students ($N = 298$) reported on their preferences for 11 learning formats and the expected added value of their preferred formats. We found five groups with different preference profiles: One favoring all formats and four with more selective preferences – including groups preferring only explainer videos, game-based learning, or eye tracking and emotion recognition alongside other formats. Across all groups, explainer videos, virtual classrooms and laboratories, machine learning, chatbots as examiners, and serious games were the most popular formats. While groups differed in format preferences, they showed similar perceptions of each format's added value, suggesting that differences reflect varying learning approaches rather than differing views on format effectiveness.

Keywords: digital higher education; digital learning formats; student preferences.

Zusammenfassung

Digitale Lernformate können zu einer besseren Hochschullehre beitragen. Der Einsatz dieser Formate in zukünftiger Lehre, die Extended Reality, Gaming und künstliche Intelligenz nutzen, soll sich nicht nur an technischen Möglichkeiten orientieren, sondern auch an Präferenzen und Bewertungen der Studierenden. Studierende der Informatik und des Ingenieurwesens ($N = 298$) berichteten ihre Präferenzen für 11 Lernformate und den erwarteten Mehrwert der von ihnen bevorzugten Formate. Wir fanden fünf Gruppen mit unterschiedlichen Präferenzprofilen: Eine Gruppe, die alle Formate bevorzugt, und vier Gruppen mit selektiveren Präferenzen - darunter Gruppen, die nur Erklärvideos, Game-Based Learning oder Eye-Tracking und Emotionserkennung neben anderen Formaten bevorzugten. Über alle Gruppen hinweg waren Erklärvideos, virtuelle Seminarräume und Labore, maschinelles Lernen, Chatbots als Prüfer und Serious Games die beliebtesten Formate. Die Gruppen unterschieden sich zwar in ihren Formatpräferenzen, schätzten aber den Mehrwert der Formate ähnlich ein. Dies deutet darauf hin, dass Unterschiede eher auf unterschiedliche Lernzugänge als auf unterschiedliche Ansichten über die Wirksamkeit der Formate zurückzuführen sind.

Schlüsselwörter: Digitale Hochschullehre; digitale Lernformate; Präferenzen Studierender.

1. Introduction

Technological progress influences many areas of our lives, including higher education. The question is not whether education will become more digital, but how to strategically leverage digital technologies to enhance the quality of higher education learning and teaching (Conway et al., 2015). To achieve high-quality education, strategies should be informed not only by technical possibilities but also by students' preferences and expectations concerning different digital learning formats. In our study, we focused specifically on preferences and expectations concerning digital formats that may be implemented or used more frequently in future higher education. Eleven formats were selected based on a publication by the Federal Institute for Vocational Education and Training (Christ et al., 2020). We asked students enrolled in computer science and engineering departments whether these formats should be made available at their university and to what extent they were interested in testing these formats. The study addressed four research questions (RQ):

- RQ1: Which digital learning formats should be incorporated into future higher education?
- RQ2: What added value do students attribute to the formats which they would like to see incorporated and to test?
- RQ3: Are there student groups with different format preferences?
- RQ4: If there are multiple groups, do they differ in their evaluation of formats and in personal characteristics?

Despite the availability of a broad range of digital resources, many students still prefer using a limited selection of familiar working methods such as electronic texts and videos (Noskova et al., 2021; Wilhelm-Chapin & Koszalka, 2020; Sutherland et al. 2024). The potential of digital technologies for collaboration, knowledge exchange, and knowledge extraction has been insufficiently exploited so far. The development of new digital learning formats offers higher educational institutions an opportunity to enhance student engagement and learning outcomes. Immersive interfaces such as virtual and augmented reality can provide students with authentic learning environments that teach procedural-practical knowledge (Radianti et al., 2020) and facilitate collaboration, social interaction, and creativity (Hew & Cheung, 2010). Game-based learning and gamification increase motivation and enjoyment and help develop 21st century skills such as creativity and collaboration (Coleman & Money, 2020; Krath et al., 2021; Qian & Clark, 2016; Saleem et al., 2022). Chatbots can provide instant, personalized feedback and increase engagement (Hobert, 2023; Winkler & Soellner, 2018; Wollny et al., 2021). AI offers personalized learning experiences and feedback (Roll & Wylie, 2016).

Understanding students' preferences regarding digital learning formats can help design e-learning environments (e.g., Pechenkina & Aeschliman, 2017). However, implementing new formats requires resources, and their selection should be informed by their expected advantages over existing formats. Using digital tools and media, per se, is not more or less effective than using more traditional tools and media (see the studies featured in the No Significant Difference database; National Research Center for Distance Education and Technological Advancement, 2019). We therefore asked participants about both their preferences and the potential added value (e.g., better learning, more practical relevance, greater flexibility) of their preferred learning formats.

In addition to considering diverse learning formats, we need to consider heterogeneous student populations not only in terms of age, gender, socioeconomic status, and special educational needs, but also in terms of their preferences in learning formats. For example, Kuzmanović et al. (2019) identified two groups of students: One group focused on the process of learning, liked to use the e-learning environment in a flexible and interactive manner, and preferred classroom live broadcasting. The other group was more interested in assessing their own learning results, wanted clear deadlines for assignments, and preferred recorded lectures.

Contrary to what Prensky's designation as *digital natives* (2001) suggests, we cannot treat today's student population as a unified cohort with learning needs completely different from those of previous cohorts (Evans & Robertson, 2020). Even digital natives can have a preference for non-digital formats for lectures and working on team projects, and preferences for digital feedback and discussions vary depending on prior experience with online courses (Goodson et al., 2018). If we are to adjust our pedagogy to students' literacy, experiences, and preferences in digital technology usage, we first need to explore how heterogeneous their interests are.

2. Method

The study was conducted online in February 2021 using formr (Arslan et al., 2020). Materials and data are available in the Open Science Framework (OSF; Schindler et al., 2025).

Participants first provided informed consent. As the study was done during the COVID-19 pandemic, participants were instructed to respond based on their typical behavior rather than pandemic restrictions. Ten randomly selected participants received 20-Euro vouchers as compensation.

The survey consisted of five sections: (1) demographic information, (2) digital media literacy and usage, (3) personal views on learning and the distribution of tasks between students and teachers, (4) current use of learning materials, and (5) preferences and expectations for 11 future digital learning formats plus the option to make an own suggestion for a 12th format. The number of questions asked varied between participants, depending on their selection of formats. There were 22 additional questions for each selected format that students were interested in testing. The total number of questions ranged from 74 (only one format selected) to 316 (all 12 formats selected). Reflecting this range in the number of questions, completing the questionnaire took between 25 and 45 minutes. Our analysis focused on Part 5 with data from Parts 1, 2, and 4 serving as background information; data from Part 3 were not relevant for addressing our research questions.

2.1. Participants

We recruited bachelor's and master's students from four technology-related departments – computer science, engineering sciences, industrial engineering and technology management, and energy, environmental, and process engineering – at a University of Applied Sciences for distance learning. Of the 349 students who accessed the survey, 326 began answering it, and 267 completed it. Our analyses include all 298 participants who selected at least one learning format for future implementation. A few of these participants' responses on the added value of their preferred formats are missing, because they aborted the survey prematurely. Figure 1 provides information on participants' gender, education, and employment, Figure 2 on age, self-rated media competence, and media use.

Variable	Valid responses	*n*	%	Scaling and range of variable
Gender	298			Categories (1-4)
1 Female		88	29.53	
2 Male		208	69.80	
3 Diverse		1	0.34	
4 No response		1	0.34	
Highest educational degree	298			Categories (1-9)
1 State-certified technical engineer		30	10.07	
2 Certified master craftsman/bachelor professional		13	4.36	
3 University of applied sciences entrance qualification		58	19.46	
4 University entrance qualification		87	29.19	
5 Bachelor's degree		58	19.46	
6 Master's degree		13	4.36	
7 Diploma degree		10	3.36	
8 Doctoral degree		3	1.01	
9 Other degree (e.g., intermediate school-leaving certificate, vocational school certificate, vocational training)		26	8.72	
Current degree program	292			Based on course of study
Bachelor's degree		245	82.21	
Master's degree		56	18.79	
Current field of study	292			Categories (1-4; based on course of study)
1 Computer science		120	41.10	
2 Engineering sciences		96	32.88	
3 Industrial engineering and technology management		49	16.78	
4 Energy, environmental, and process engineering		27	9.25	
Employment and occupation (besides studying)	294			Checkboxes (multiple choice)
No other employment/occupation		10	3.40	
Full-time employment		234	79.59	
Part-time employment		47	15.99	
Self employed		18	6.12	
Raising children		26	8.84	
Caregiving for relatives		5	1.70	
Volunteer work		47	15.99	
Other occupation (e.g., 450-Euro job, housebuilding/renovation, competitive sports)		10	3.40	

Figure 1. Sample description: Gender, education, and employment.

Variable	Valid responses	*M*	*SD*	Scaling and range of variable
Age	297	30.42	7.53	Years (18-63)
Digital media competence (self-rated)	296	3.90	0.84	Rating (1-5)
Frequency of private digital media use				
Receptive use	298	4.00	0.54	Average rating (1.60-5.00)
Listening to the radio, music	296	4.58	0.86	Rating (1-5)
Listening to podcasts, audio books	297	3.04	1.53	Rating (1-5)
Reading newspapers, magazines, books, articles, news	298	4.39	0.95	Rating (1-5)
Watching videos, movies, TV, streaming services (e.g., YouTube, Netflix)	297	4.69	0.60	Rating (1-5)
Online Shopping	296	3.30	0.76	Rating (1-5)
Interactive use	298	3.05	0.62	Average rating (1.43-5.00)
Writing texts, creating presentations	296	3.66	1.17	Rating (1-5)
Recording, creating, and editing videos, photos, drawings, or music	295	2.87	1.27	Rating (1-5)
Using social media (e.g., Twitter, Instagram, Facebook)	297	3.80	1.60	Rating (1-5)
Communication via chat rooms, video conferencing, etc.	297	3.98	1.17	Rating (1-5)
Using online 3D infrastructures (e.g., Second Life)	295	1.28	0.73	Rating (1-5)
Playing games/gaming (online and/or offline)	297	2.95	1.47	Rating (1-5)
Programming, creating applications	298	2.78	1.51	Rating (1-5)
Other uses (e.g., organizing with google calendar, communicating via email and WhatsApp, searching for information)	230	1.48	1.20	Rating (1-5)
Frequency of use of learning materials				
Learning materials and resources offered by the university				
Printed documents (e.g., scripts, manuscripts, study books, books)	297	4.31	1.06	Rating (1-5)
Digital resources (availability depends on modules)	298	2.88	0.75	Average rating (1.00-5.00)
Digital documents (e.g., e-books, scripts, manuscripts / study books in pdf, html, epub etc.)	298	4.11	0.97	Rating (1-5)
Videos accompanying specific topics / study books / modules (e.g., explainer videos)	297	3.33	1.24	Rating (1-5)
Online learning maps / cards	296	1.70	1.08	Rating (1-5)
Databases of the internal online campus (e.g., Springer Link, ACM, EBSCOhost Research Databases, GI)	297	2.38	1.12	Rating (1-5)
Other learning materials and resources	298	3.51	0.75	Average rating (1.67-5.00)
Other online databases and networks (e.g., Google Scholar, ResearchGate, IEEE)	298	2.63	1.34	Rating (1-5)
Online encyclopedias and reference works (e.g., Wikipedia, dictionaries)	296	3.90	0.90	Rating (1-5)
Online videos and tutorials (e.g., YouTube)	298	4.00	0.95	Rating (1-5)
Other materials and resources (e.g., learning apps, online courses offered by Udemy, Studyflix, or Sofatutor, AnkiDroid cards, online forums and platforms such as Stack Overflow and LinkedIn, scientific journals)	194	1.62	1.27	Rating (1-5)

Figure 2. Sample description: Age and media use.

2.2. Measures

Digital media literacy and media use (Figure 2): Participants reported above-average digital media competence (M = 3.90) on a five-point Likert scale (1 = *not good at all* to 5 = *very good*). They rated their frequency of digital media use outside educational contexts for 13 different activities on a scale from 1 (*never*) to 5 (*almost daily*). We aggregated the different types of digital media use into two variables: (1) receptive and (2) interactive use. Receptive use included activities where existing content was viewed, listened to, or accessed, but not modified. Interactive use involved creating or modifying content.

Use of learning materials (Figure 2): Participants reported on their current frequency of use of learning materials provided by their university and of additional online resources on a five-point scale (1 = *never* to 5 = *almost daily*). When interpreting the frequency scores, it is important to note that not all modules of the study programs offered specific digital resources, and that only printed materials were offered in all modules. We created three variables: (1) frequency of use of printed university-offered learning materials (a single item), (2) average frequency of use of digital university-offered learning materials, and (3) average frequency of use of non-university digital learning materials.

Future digital learning formats evaluated in the study:

1. audio versions accompanying study books;
2. explainer videos;
3. virtual classrooms;
4. virtual laboratories;
5. digital learning games / serious games;
6. gamification;
7. chatbots as virtual tutors;
8. chatbots as virtual examiners / trainers;
9. machine learning using Artificial Intelligence (AI);
10. eye tracking;
11. face and emotion recognition.

For the formats 3-11, we provided explanations of how these technologies can be used in teaching. Participants could suggest a 12th format (e.g., digitally recorded lectures, automatic recognition of familiarity with a topic and adaptive choice of further learning content, chatbots as lecturers, multiple-choice online tests, computer-generated questions with checking of the solutions or with an indicated solution path, learning apps, and hackathons).

Participants selected all formats that should be offered in the future. For each selected format, they rated their interest in testing the format on a five-point Likert scale (1 = *not at all* to 5 = *very much*). All participants who had rated personal interest with 4 or 5 were asked additional questions on the expected added value of this format (Figure 3), resulting in 281 participants who answered additional questions for at least one format. The number of rated formats per participant ranged from 1 to 11 (M = 4.14, SD = 2.27).

Item	Valid responses	*M*	*SD*	ICC format	ICC person
Better learning (α = .82)	1162	4.15	0.80	.19	.20
Acquire knowledge more easily and retain it better	1159	4.17	0.86	.26	.15
Learn faster and more effectively	1161	4.13	0.87	.11	.22
Achieve better exam results	1153	4.09	0.87	.09	.33
More satisfaction (α = .83)	1158	4.06	0.82	.11	.37
Be more satisfied with the learning process	1157	4.14	0.82	.06	.35
Be more satisfied with learning materials and learning environments	1154	3.97	0.94	.14	.31
Better understand, explain, and discuss what you have learned	1152	4.05	0.96	.33	.15
Be more motivated in learning	1155	4.05	0.88	.18	.25
Get more individualized instruction and feedback	1154	3.73	1.17	.23	.16
More practical relevance (α = .88)	1155	3.68	1.08	.34	.22
Have more opportunities for practical testing and experimentation	1152	3.69	1.17	.33	.20
Better practical application and creative use of what you have learned	1150	3.67	1.12	.29	.22
Be more flexible and self-determined in the choice of working hours, locations, and techniques	1151	3.58	1.30	.13	.40
More interaction (α = .92)	1155	3.08	1.30	.35	.28
Have more interaction and exchange with teachers	1148	3.16	1.34	.33	.25
Have more interaction and exchange with other students	1153	3.00	1.36	.32	.28

Note. α = Cronbach's alpha. ICC = intraclass correlation. All ICCs were significant: 95% credibility interval did not include 0. The values are based on ratings of the 11 formats and exclude ratings for "other format."

Figure 3. Item overview: Expected added value of formats.

2.3. Data analysis

IBM SPSS Statistics (version 24) and M*plus* (version 8.4) were used for data analysis. To investigate RQ3 concerning preference groups, we conducted a latent class analysis (LCA) in M*plus* using the 11 digital learning format choices as binary variables (0 = *not selected*, 1 = *selected*).

LCA identifies groups (latent classes) of participants with: (1) maximum similarity of selection profiles within groups and (2) maximum differences between groups. To determine the optimal number of classes, we estimated models with one to five classes and evaluated fit using Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC. We also assessed classification accuracy using entropy and average latent class probabilities for the most likely latent class membership (AvePP). Likelihood Ratio Tests (LRT) determined if additional classes significantly improved fit. Models with more than five classes were not considered as they produced groups with less than 5% of participants and poor identification. Lower values for fit indices and *p*-values indicate better fit, while higher values for entropy (range 0–1) and AvePP indicate better fit. Values of entropy greater than .800 and AvePP greater than .700 suggest good classification accuracy and well-separated classes (Masyn, 2013; Nylund-Gibson & Choi, 2018).

3. Results

Analyses to address RQ1, RQ3, and RQ4 (personal characteristics) were conducted with the full sample of 298 participants. Analyses of the added value of formats to address RQ2 and RQ4 (evaluation of formats) were performed with the sample of 281 participants who rated at least one format.

3.1. RQ1: Future digital learning formats

Figure 4 shows the percentage of participants selecting each format (numbers in grey boxes). Videos and virtual classrooms were the most popular formats, eye tracking and emotion recognition were least popular. The bars were divided into participants who selected formats but were not interested in testing them (red sections: interest ≤ 3) and those interested in testing (green sections: interest > 3). The black line displays the average interest ratings, showing a general trend of decline along with the declining frequency of format choice. Even those participants who selected one of the less popular formats reported lesser interest in testing it compared with their interest in testing more popular formats. Two exceptions were audio versions and "other" format, which received high interest ratings.

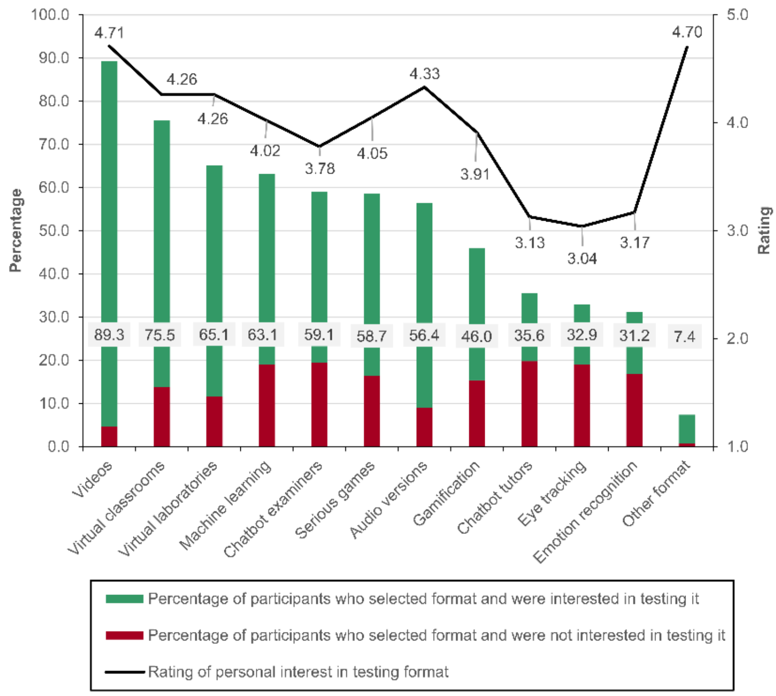


Figure 4. Percentage of participants selecting formats and interest in testing formats.

3.2. RQ2: Added value of learning formats

When analyzing the expected added value of formats, we considered that most participants (86.1%) rated multiple formats and that the ratings reflect not only differences between formats but also between participants. Intraclass correlations (ICCs; Figure 3) showed that 6-40% of the variance in item ratings was attributable to similarities in how different participants evaluated the same format (ICC format) or how the same participant evaluated different formats (ICC person).

We used two types of variables to assess differences in the added value of formats: (1) raw value ratings and (2) centered value ratings (difference between a participant's rating of a specific format and their average rating across all selected formats). Both multivariate analyses of variance showed significant differences between formats: raw ratings $F(90, 10089) = 15.03$, $p < .001$, $\eta_p^2 = .12$; centered ratings $F(90, 10089) = 16.02$, $p < .001$, $\eta_p^2 = .13$. All univariate tests for the individual variables also were significant (Figure 5).

Figure 6 illustrates differences in expected added value across formats. Figure 5 presents format groups without significant value rating differences. Videos scored highest for better learning, exam results, satisfaction, and understanding. Serious games and gamification showed greatest potential for motivation. Virtual classrooms and laboratories, eye tracking, and chatbots were perceived best for individualized instruction. Virtual laboratories and serious games were rated highest for practical relevance. Audio versions and chatbots offered greatest flexibility, while virtual classrooms and laboratories provided most interaction opportunities.

Variable	$F(10, 1121)$	p	η_p^2	Groups of formats that are not significantly different from each other[a]
Raw ratings				
Better learning	16.37	< .001	.13	1) VI, VL, GA 2) VL, GA, SG, AV, VC, ML 3) GA, SG, AV, VC, ML, CT 4) VC, ML, CT, ET 5) ML, CT, ET, CE 6) CT, ET, CE, ER
Better exam results	4.09	< .001	.04	1) VI, VL, CE, VC, SG, ML, GA, CT, ET 2) VL, CE, VC, SG, ML, GA, CT, ET, AV 3) SG, ML, GA, CT, ET, AV, ER
More satisfaction	5.87	< .001	.05	1) VI, VL, GA, SG, VC, AV, CT, ET 2) VL, GA, SG, VC, AV, CT, ET, ER 3) GA, SG, VC, AV, CT, ET, ER, CE 4) AV, CT, ET, ER, CE, ML
Better understanding	32.34	< .001	.22	1) VI, VC, VL 2) VL, CT 3) SG, CT, GA, AV, ML 4) CT, AV, ML, CE 5) CE, ER, ET
More motivation	8.23	< .001	.07	1) SG, GA, VL, VI, VC 2) GA, VL, VI, VC, AV 3) VL, VI, VC, AV, ET 4) VC, AV, ML, CE, ET, CT, ER
More individualized instruction	26.62	< .001	.19	1) VC, VL, CE, CT, ET 2) VL, CE, CT, ET, ML, ER 3) CE, CT, ET, ML, ER, SG, GA 4) ER, GA, VI 5) VI, AV
More practical relevance	34.26	< .001	.23	1) VL, SG, GA 2) SG, GA, VC 3) GA, VC, VI 4) VI, CE, ML, CT 5) ML, CT, AV 6) CT, AV, ER, ET
More flexibility	8.94	< .001	.07	1) AV, CE, CT 2) CE, CT, SG, VI, ML, GA, VL, ET

Variable	$F(10, 1121)$	p	η_p^2	Groups of formats that are not significantly different from each other[a]
				3) CT, SG, ML, GA, VL, ET, VC 4) ET, VC, ER
Continued on the next page				
More interaction	47.99	< .001	.30	1) VC, VL 2) SG, GA, CT 3) GA, CT, VI, CE 4) CT, VI, CE, ML, AV, ER 5) CT, CE, ML, AV, ER, ET
Centered ratings				
Better learning	22.27	< .001	.17	1) VI 2) VL, SG, GA, AV, VC, ML 3) GA, AV, VC, ML, CT 4) ML, CT, ET 5) CT, ET, CE, ER
Better exam results	7.19	< .001	.06	1) VI, VC, VL, CE, CT 2) VC, VL, CE, ML, SG, GA, CT, AV 3) SG, GA, CT, AV, ET, ER
More satisfaction	10.93	< .001	.09	1) VI, VL, SG, GA, VC 2) VL, SG, GA, VC, AV, CT, ET 3) VC, AV, CT, ET, ER 4) CT, ET, ER, ML, CE
Better understanding	34.09	< .001	.23	1) VI, VC, VL 2) VC, VL, CT 3) VL, CT, SG, GA 4) CT, SG, GA, ML, AV 5) ML, AV, CE, ER 6) CE, ER, ET
More motivation	11.95	< .001	.10	1) SG, GA, VL, VI, VC 2) GA, VL, VI, VC, AV 3) AV, ML, CE, CT, ER, ET
More individualized instruction	28.58	< .001	.20	1) VC, VL, ET, CT 2) VL, ET, CE, CT, ML, ER 3) CE, ET, CT, ML, ER, SG, GA 4) ER, GA, VI 5) AV
More practical relevance	39.20	< .001	.26	1) VL, SG 2) SG, GA, VC 3) GA, VC, VI 4) VI, CE, CT 5) CE, ML, CT 6) CT, AV, ER 7) AV, ER, ET
More flexibility	16.35	< .001	.13	1) AV 2) CE, VI, SG, CT, ML, GA, VL, ET 3) CT, GA, VL, ET, VC 4) ET, ER
More interaction	61.89	< .001	.36	1) VC 2) VL 3) SG, GA, CT 4) CT, VI, CE, AV, ML, ER, ET

Note. Raw average ratings: range 1-5. Centered ratings were computed by subtracting the participant's average item rating across all formats from the rating of each format. VI = videos, VC = virtual classrooms, VL = virtual laboratories, ML = machine learning, CE = chatbot examiners, SG = serious games, AV = audio versions, GA = gamification, CT = chatbot tutors, ET = eye tracking, ER = emotion recognition.
[a] Based on post-hoc Tukey tests with Bonferroni correction.

Figure 5. ANOVA: Differences in expected added value of formats.

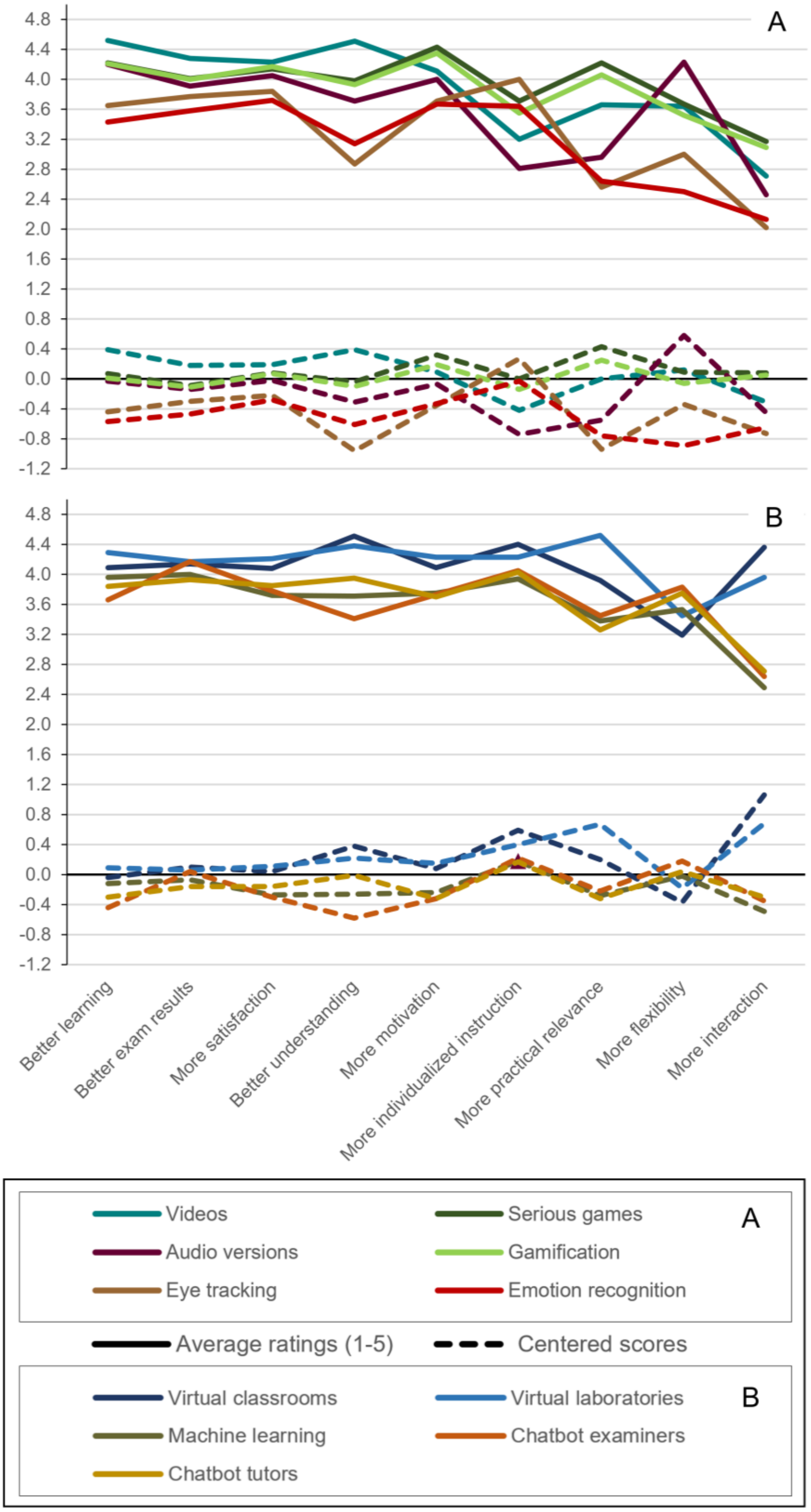


Figure 6. Expected added value of formats.

3.3. RQ3: Groups with different preference profiles

The fit indices for the tested LCA models (Figure 7) indicate more than one class (participant group). The indices did not clearly recommend a specific number of groups – for instance, the three-class model had the best BIC value but lowest entropy. Considering all indices and group interpretability, we selected the five-class model, which had the best values for AIC and sample-size adjusted BIC and was in the middle range for all other indices.

	Number of classes				
Fit index	**1**	**2**	**3**	**4**	**5**
AIC	4097	3517	3448	3416	3395
BIC	4138	3602	3577	3589	3613
Sample-size adjusted BIC	4103	3529	3466	3440	3426
Entropy	-	.926	.793	.893	.847
AvePPclass1	1.000	.943	.809	.990	1.000
AvePPclass2	-	.991	.991	.953	.920
AvePPclass3	-	-	.933	.930	.852
AvePPclass4	-	-	-	.888	.927
AvePPclass5	-	-	-	-	.840
Vuong-Lo-Mendell-Rubin LRT: p-value	-	< .001	.008	.251	.051
Vuong-Lo-Mendell-Rubin corrected LRT: p-value	-	< .001	.008	.257	.053

Note. - statistic is not applicable to this model. AIC = Akaike's Information Criterion. BIC = Bayesian Information Criterion. AvePP = average latent class probability for the most likely latent class membership. LRT = likelihood ratio test.

Figure 7. LCA: Model comparison.

The five identified preference groups differed in their format selection probabilities, with one exception (Figure 8): all groups preferred videos. Group 5 labeled "video only" (*n* = 76; 25.5%) sticks out by selecting only this format with over 50% probability. The other four groups all selected videos, virtual classrooms, virtual laboratories, machine learning, and chatbot examiners with over 55% probability.

Selection of the remaining six formats varied between groups. Group 1 ("all formats"; *n* = 64; 21.5%) frequently selected all formats. Group 3 ("virtual reality focus"; *n* = 83; 27.9%) chose the five commonly preferred formats but rarely selected the remaining six, following the overall sample pattern. Groups 4 and 2 resembled Group 3 in their preference for the five common formats but showed additional distinct preferences. Group 4 ("game focus"; *n* = 54; 18.1%) frequently chose gamification, serious games, and audio versions, while avoiding potentially controlling formats (eye tracking and emotion recognition). Group 2 ("process feedback focus"; *n* = 21; 7.0%) frequently selected eye tracking and emotion recognition.

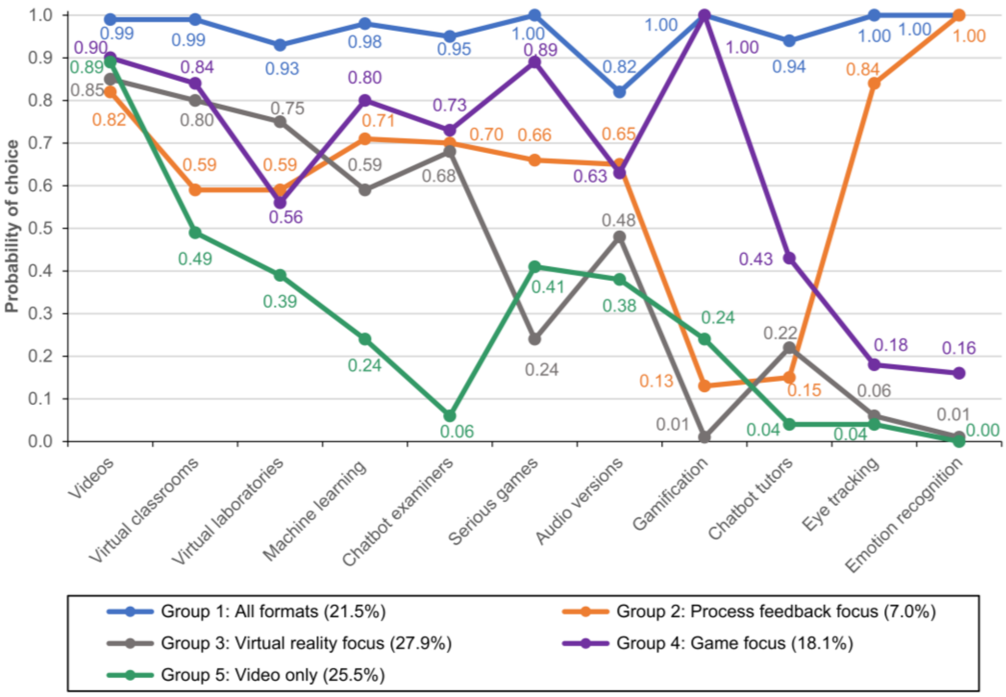


Figure 8. Format preference profiles of five groups.

3.4. RQ4: Differences between preference groups

Our last research question concerned differences between the five preference groups. Among all participants selecting a format, differences in interest in testing a format are evident between formats, but we found only few interest differences between preference groups (Figures 9 and 10). The highest interest was in videos, virtual classrooms, and virtual laboratories, with lowest interest in chatbot tutors, eye tracking, and emotion recognition. This pattern was evident even in the "all formats" Group 1: the 43 (out of 64) participants in this group selecting all 11 formats showed significant differences in their interest ratings across formats, $F(10, 420) = 25.02$, $p < .001$, $\eta_p^2 = .37$. Deviation contrasts revealed above-average interest in videos, $F(1, 42) = 147.95$, $p < .001$, $\eta_p^2 = .78$, virtual classrooms, $F(1, 42) = 22.15$, $p < .001$, $\eta_p^2 = .35$, virtual laboratories, $F(1, 42) = 17.03$, $p < .001$, $\eta_p^2 = .29$, and machine learning, $F(1, 42) = 11.58$, $p = .001$, $\eta_p^2 = .22$. Chatbot tutors, $F(1, 42) = 62.16$, $p < .001$, $\eta_p^2 = .60$, eye tracking, $F(1, 42) = 45.13$, $p < .001$, $\eta_p^2 = .52$, and emotion recognition, $F(1, 42) = 30.00$, $p < .001$, $\eta_p^2 = .42$, were rated below average.

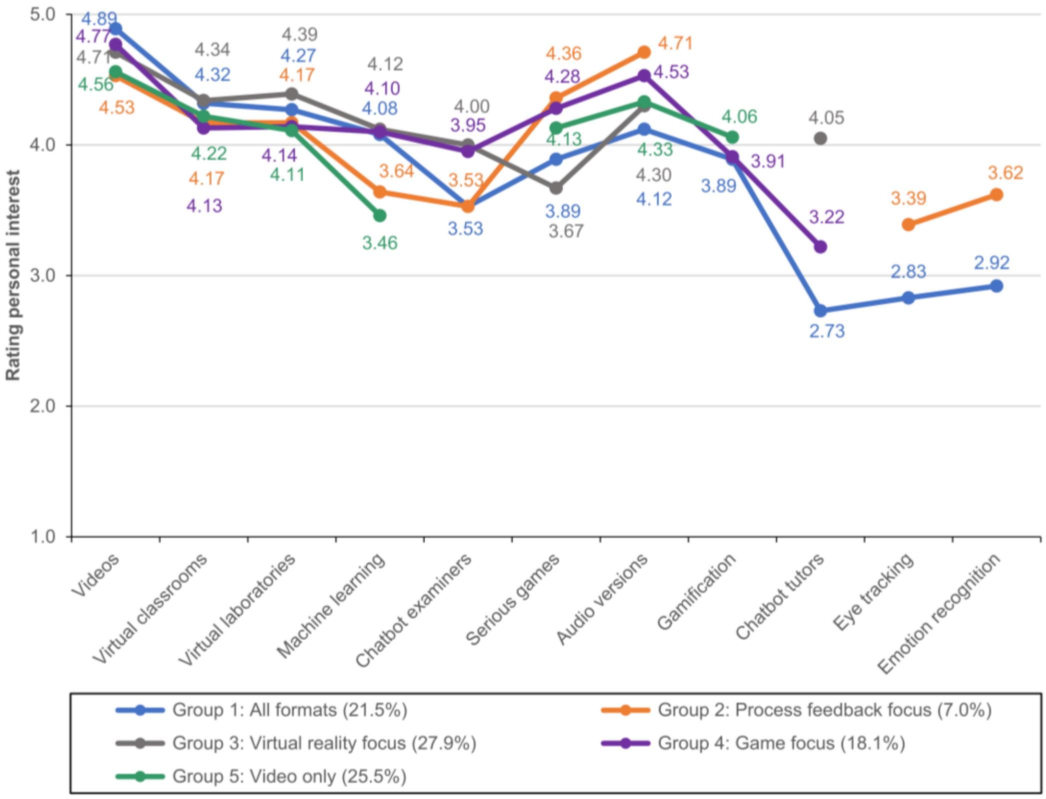


Figure 9. Interest in testing formats by preference group.

The group comparisons (Figure 10) using pairwise post-hoc Tukey tests with Bonferroni correction showed that participants in the "all formats" Group 1 were significantly more interested in testing videos than participants in the "video only" Group 5. Even though participants in Group 1 chose chatbot tutors more frequently than participants in the "virtual reality focus" Group 3, they were significantly less interested in testing them than the few participants in Group 3 who had chosen them. The findings overall suggest that participants who selected a learning format were similarly interested in testing it, regardless of which preference group they belong to.

Variable	*F*	*df1*	*df2*	*p*	η_p^2	Preference groups that were not significantly different from each other[a]
Videos	3.58	4	258	.007	.05	1) G1, G2, G3, G4 2) G2, G3, G4, G5
Virtual classrooms	0.63	4	220	.639	.01	1) G1 – G5
Virtual laboratories	0.75	4	189	.557	.02	1) G1 – G5
Machine learning	2.01	4	177	.095	.04	1) G1 – G5
Chatbot examiners (without G5)	3.10	3	171	.028	.05	1) G3, G4, G2, G1 [G3 > G1 at p = .052]
Serious games	1.99	4	169	.099	.05	1) G1 – G5
Audio versions	1.89	4	162	.114	.05	1) G1 – G5
Gamification (without G2 & G3)	0.17	2	132	.847	.00	1) G1, G4, G5
Chatbot tutors (without G2 & G5)	8.14	2	98	.001	.14	1) G3, G4 2) G4, G1
Continued on the next page						

Variable	*F*	*df1*	*df2*	*p*	η_p^2	Preference groups that were not significantly different from each other[a]
Eye tracking (without G5)	1.47	3	91	.229	.05	1) G1, G2, G3, G4
Emotion recognition (without G3 & G5)	2.92	2	88	.059	.06	1) G1, G2, G4

Note. Groups with < 5 participants rated the format were excluded from the analysis of this format. Excluded groups are noted in parentheses. G1 = Group 1: All formats, G2 = Group 2: Process feedback focus, G3 = Group 3: Virtual reality focus, G4 = Group 4: Game focus, G5 = Group 5: Video only.
[a] Based on post-hoc Tukey tests with Bonferroni correction.

Figure 10. ANOVA: Group differences in interest in testing formats.

Next, we tested for group differences in evaluations of formats' added value. As we did not find significant differences in participants' average ratings across all 11 formats in a multivariate analysis of variance including the nine added value variables, $F(36, 1076) = 1.16$, $p = .237$, $\eta_p^2 = .04$, we tested only for differences in raw ratings (not centered ratings). All univariate tests for the 11 formats were nonsignificant (*p*-values between .083 and .901). While the groups differed in their selection of formats, they agreed on the added value of the formats.

Finally, we examined differences in demographic characteristics and current use of digital media and learning materials between preference groups. There were no differences in the percentage of men per group (Figure 11), average age, and self-reported digital media competence (Figure 12).

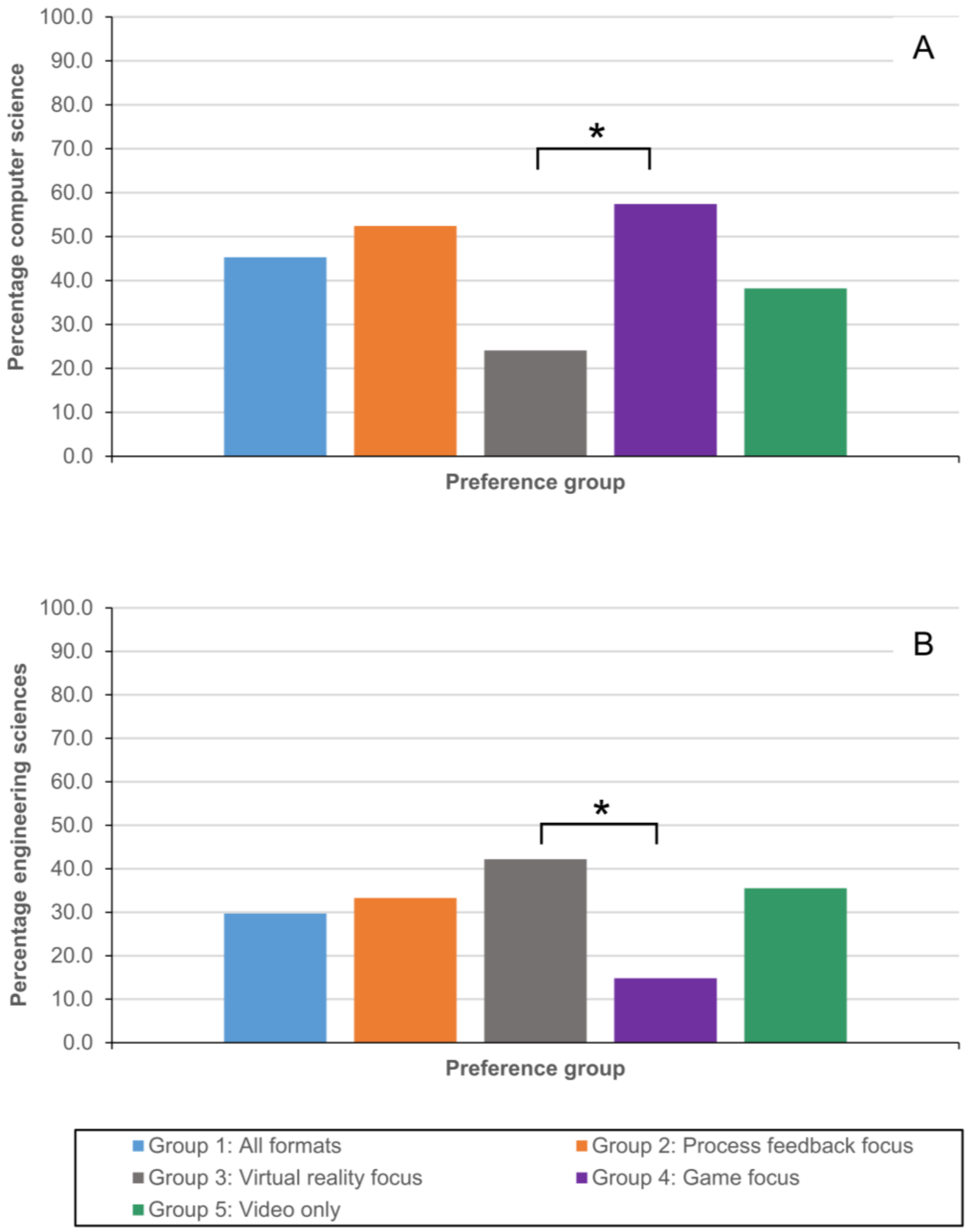
Significant associations emerged between group membership and field of study, $\chi^2(12) = 26.30$, $p = .010$, Cramer's V = .17. Separate analyses by field (Figure 11) revealed that computer science students were underrepresented in the "virtual reality focus" Group 3 and overrepresented in the "game focus" Group 4 (Figure 13A). Engineering students showed the opposite pattern, with higher representation in Group 3 and lower representation in Group 4 (Figure 13B).

Variable	χ^2	*df*	*p*	Cramer's V
Gender: male	7.69	4	.103	.16
Field of study				
Computer science	17.72	4	.001	.24
Engineering sciences	11.83	4	.019	.20
Industrial engineering and technology management	2.01	4	.734	.08
Energy, environmental, and process engineering	6.64	4	.156	.15

Figure 11. Group differences in gender and field of study.

Variable	*F*	*df1*	*df2*	*p*	η_p^2
Age	0.56	4	292	.689	.01
Digital media competence	0.20	4	291	.940	.00
Frequency of private digital media use					
Receptive use	0.40	4	293	.809	.01
Interactive use	3.29	4	293	.012	.04
Frequency of use of learning materials					
Printed documents offered by the university	1.47	4	292	.210	.02
Digital resources offered by the university	3.16	4	292	.014	.04
Other learning materials and resources	1.30	4	292	.272	.02

Figure 12. ANOVA: Group differences in age, media competence, and use of media and learning materials.

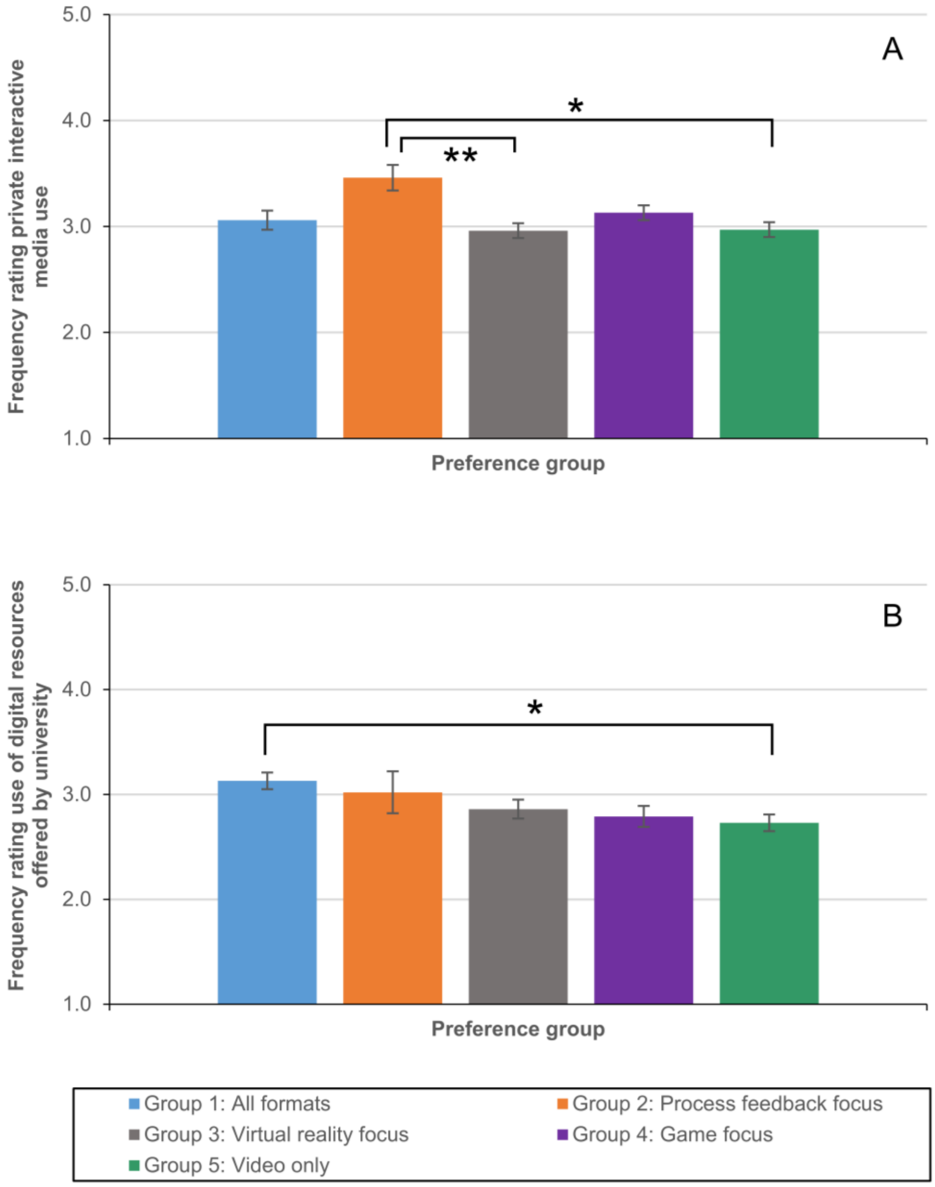


Note. * Significant difference at $p < .05$.

Figure 13. Group differences in enrollment in computer science (A) and engineering sciences (B).

Further group differences emerged regarding digital media use outside educational contexts. Although the multivariate analysis for receptive and interactive use was not significant, $F(8, 586) = 1.79$, $p = .077$, $\eta_p^2 = .024$, the univariate test for interactive use was (Figure 12). "Process feedback focus" Group 2 participants reported monthly to weekly interactive use, while "virtual reality focus" Group 3 and "video only" Group 5 participants reported monthly or less frequent use (Figure 14A).

Similarly, the multivariate analysis of variance for current learning materials usage was not statistically significant, $F(12, 876) = 1.60$, $p = .087$, $\eta_p^2 = .021$, but univariate testing revealed differences in university-offered digital materials usage (Figure 12). "All formats" Group 1 participants used university-offered digital resources more frequently than "video only" Group 5 participants (Figure 14B), suggesting that Group 1's greater interest in future digital formats corresponds with their current digital learning habits.



Note. Significant difference at * $p < .05$. ** $p < .01$.

Figure 14. Group differences in private interactive media use (A) and use of university-offered digital resources (B).

4. Discussion

The study highlighted that there is no one-size-fits-all approach to digital learning formats.

It identified five groups of participants with distinct preferences for future digital education, yet no group differences in the expected added value of different formats.

4.1. Students' wishes and expectations for future learning formats

Most participants (except "video only" Group 5) preferred five learning formats: videos, virtual classrooms, virtual laboratories, machine learning, and chatbot examiners. Biometric technologies (eye tracking and emotion recognition) were least popular. The added value attributed to all preferred learning formats was better exam results, suggesting that most students' learning format selection was informed by the potential to enhance academic success. Videos and virtual rooms also shared the added values of better learning, more satisfaction, better understanding, and more motivation. The only added value associated primarily with biometric technologies (and virtual rooms and chatbots) was more individualized instruction.

"All formats" Group 1 participants wanted all 11 learning formats offered and already used university-offered digital materials more frequently than "video only" Group 5. This reflects greater openness to digital formats and / or enrollment in programs offering more digital materials, as experience with digital resources correlates with preference for them (Goodson et al., 2018).

"Game focus" Group 4 preferred serious games and gamification, suggesting interest in learning formats with added values such as more motivation, satisfaction, and practical relevance. Computer science students were overrepresented in this group. Only the small "process feedback focus" Group 2 showed specific interest in eye tracking and facial and emotion recognition. This group reported interactive use of digital media outside education more frequently than Groups 3 and 5.

These findings indicate general student interest in digital formats, while not all formats were evaluated as equally promising. However, our sample included only students from technology-oriented departments, potentially biasing results toward greater technological interest. Buzzard et al. (2011) found higher interest in instructional technologies among engineering students compared to those in education, social sciences, and humanities.

The popularity of videos aligns with previous research showing preferences for learning and explainer videos and recorded lectures (Noskova et al., 2021; Wilhelm-Chapin & Koszalka, 2020; Sutherland et al., 2024). While students of all universities favor videos, the high interest in virtual classrooms and laboratories in our sample reflect the specific needs of distance learning students. For geographically dispersed students balancing work, family and studies, digital spaces that simulate face-to-face teaching while saving time and money are particularly valuable. Nevertheless, students attending on-campus universities may also value virtual environments for their capacity to enable collaboration with diverse students and professionals across institutions, enriching the learning experience.

While integrating videos and virtual spaces into teaching is relatively straightforward, incorporating gaming elements presents more challenges due to limited didactic concepts for adult education (Miglbauer et al., 2018). Serious games in particular can be difficult to implement, as they aim to convey the entire learning content through gameplay. Gamification provides an easier way to enrich traditional learning with playful elements. Both approaches can increase motivation, evoke positive emotions, and potentially improve academic achievement (Coleman & Money, 2020; Krath et al., 2021; Qian &

Clark, 2016; Saleem et al., 2022)—the goal of most students.

Eye tracking and emotion recognition can help identify negative emotional states such as boredom, confusion, and frustration (Mejbri et al., 2022; Sharma et al., 2020), which emerge frequently during learning with technology (D'Mello, 2013). These technologies further allow to monitor students' attention and to create adaptive learning platforms that automatically recognize users' learning styles (Nugrahaningsih et al., 2021). While technically feasible through standard laptop cameras, these technologies were unpopular among most preference groups, likely due to their intrusive nature. Their harvesting of non-conscious data that reveal personal and sensitive information can be perceived as unnecessary surveillance and raise privacy concerns (Mantello et al., 2023). Notably, the "process feedback focus" Group 2's greater interest in these technologies corresponded with their more frequent interactive use of digital media, aligning with research showing that familiarity with AI correlates with more positive attitudes toward non-conscious emotional data harvesting (Mantello et al., 2023).

Participants valued chatbots for the flexibility they offer, but preferred them as examiners (59.1%) rather than tutors (35.6%). Studies have shown that the use of chatbots in teaching contexts was useful and had positive effects on engagement, satisfaction, and learning outcomes (Hobert, 2023; Winkler & Soellner, 2018; Wollny et al., 2021). Our finding suggests that chatbots are valued more for their objective assessment capabilities than for offering human-like instructional interactions and tutoring.

4.2. Limitations

Some limitations should be considered. First, data collection during the COVID-19 pandemic can have influenced participants' responses. However, the pandemic also accelerated digital transformation in education, introducing changes that may persist. Second, our convenience sample of distance learning students enrolled in computer science and engineering programs does not represent the German student population. As digital technologies become increasingly prevalent in on-campus settings, future research has to explore the generalizability of our findings. Third, the study predates ChatGPT's November 2022 launch, which has heightened expectations about AI's transformative potential in higher education. Future studies may find much greater student interest in seeing AI tools implemented in education.

4.3. Conclusions

Implementing diverse learning formats for a heterogeneous student population with diverse preferences offers opportunities but also poses challenges for higher education institutions. It is crucial to explore feasible didactic concepts that offer a balanced mix of digital and non-digital teaching methods, while also considering the costs associated with implementing and maintaining learning formats. Our study revealed student preferences for specific learning formats that they may welcome, most importantly videos, virtual environments, machine learning / AI, and chatbots. We further identified five groups with different preference profiles, with a few groups showing interest in game-based learning / gamification and eye tracking / emotion recognition. The preference profiles likely reflect differences in the kinds of incentives that can motivate individual students to adopt a learning format. Student evaluations of the learning formats' expected added value did not differ between preference groups, underscoring that group differences stem from differences in the attractiveness rather than the expectation of benefits.

The introduction of digital learning formats necessitates a comprehensive approach including training for instructors and students, as well as convincing all stakeholders of the benefits of digital technologies. Furthermore, ensuring that digital learning formats are well-developed and maintained, while sharing best practices to overcome potential challenges, will be vital for successful implementation. Although our study did not explore combinations of various digital learning formats, it is important to recognize the potential of such combinations to enhance the overall learning experience. For instance, integrating virtual laboratories with chatbots can create a more interactive and engaging learning environment. Incorporating facial and speech recognition technologies into chatbots can lead to the development of emotionally intelligent chatbots capable of recognizing users' emotions. Combining chatbots with gamification elements can provide a promising approach to enhancing student motivation.

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