Digital Presence and Learning Success: An Empirical Study on the Impact of Online Engagement on Conceptual Expertise

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Abstract: In the context of the increasing digitalization of higher education, this study examines the relationship between topic-related attendance and learning success in a fully online module in the field of media informatics. It is well known that the utilization of learning opportunities in online learning environments is generally correlated with exam success. In technically oriented online learning environments, we further investigate the extent to which such a correlation differs depending on the taxonomic levels of tasks.
The results show that the correlation of complex synthesis tasks with $r = 0.84$ is significantly higher compared to repetition tasks ($r = 0.21$) and also significantly higher compared to analysis and calculation tasks ($r = 0.11$). Both statements hold at a confidence level of 99 %. While repetition and analysis tasks were less influenced by attendance time, students who regularly and actively participated achieved significantly higher scores on tasks requiring deeper cognitive processes.

1 PROBLEM STATEMENT

The digitalization of higher education opens up new opportunities for flexible learning formats but also presents challenges, particularly in technically oriented modules. These modules require a close integration of theoretical understanding and practical application, which often leads to a gap between knowledge acquisition and actual applicability in digital formats.

The module "Audio – Video – Real-Time Networks" exemplifies this issue, as it requires both a solid understanding of fundamental concepts and their practical implementation. Students often report difficulties in transferring theoretical concepts to real-world application scenarios and recognizing the underlying structures (Bicak et al., 2023).

Reflections on online modules indicate that students who actively and regularly participated in online sessions performed significantly better in demanding tasks. However, specific studies are lacking on the extent to which online attendance, particularly in modules with analytical and synthesis-based tasks, influences student performance quality.

In particular, the relationship between online attendance and the successful completion of complex synthesis tasks compared to simpler repetition tasks remains underexplored. A detailed investigation could provide new insights into the effectiveness of

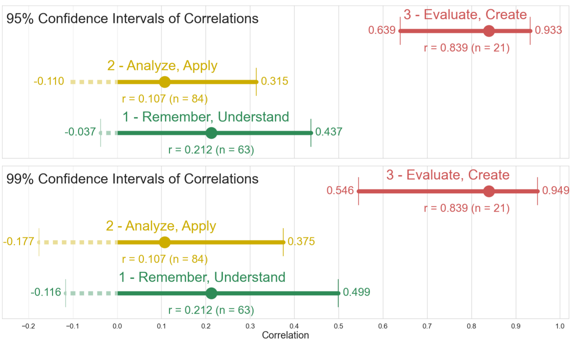

Figure 1: Main finding of the results: Correlation coefficients with confidence intervals CI_{95} and CI_{99} for all task types 1, 2, and 3. Negative values are not defined in principle. The visualization including negative values is purely for illustrative purposes and should be interpreted accordingly. Areas with negative values are drawed using a dashed pattern and whited out to emphasize this aspect.

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digital teaching methods.

This study aims to address this research gap by examining how online attendance influences students' ability to handle different cognitive demands. The findings will contribute to identifying effective teaching and learning strategies for digital formats in technical disciplines.

2 STATE OF RESEARCH

2.1 Theoretical Framework and Definition of Terms

The term *presence* derives from the Latin "praesentia" (attendance) and traditionally refers to physical co-presence in a seminar room. However, since the widespread adoption of digital teaching formats during the Covid-19 pandemic (2019), "presence" also includes virtual attendance. A distinction is made between "synchronous" and "asynchronous" participation: Synchrony refers to simultaneous attendance in a virtual space, regardless of physical location. Asynchronous participation means attending at different times (Fiedler et al., 2022, p. 2).

Hybrid teaching models combine both approaches. "Blended learning" integrates online and in-person teaching. In contrast, "hybrid teaching" refers to a format where some students are physically present while others participate online synchronously.

2.2 Impact of Social Presence on Learning Success

Social presence in online learning environments refers to the extent to which learners perceive themselves as actively engaged. It has been shown to correlate with higher course satisfaction and better performance (Decius et al., 2021). The absence of facial expressions and gestures in virtual settings can reduce social presence and negatively impact learning outcomes (Baumann, 2022, p. 73); (Orvis et al., 2010). At the same time, studies indicate that targeted, even short-term interactions can enhance social engagement and foster a sense of community among learners (Andel et al., 2020).

This implies that online courses should be designed to actively promote social presence—through interactive formats and adaptive learning environments. Integrating innovative technologies can help create a supportive online learning community that accommodates diverse learning needs.

2.3 Interaction and Learning Outcomes

Students demonstrably benefit from intensive peer interaction and reflective group activities, which lead to higher engagement and improved performance (Kuhn et al., 2021, p. 40); (Grüner, 2018, p. 95). Peer group discussions, in particular, enhance critical reflection skills (Thielmann & Böckelmann, 2021, p. 114).

This underscores the need to actively promote social interaction and connectivity in virtual learning environments to sustainably enhance learning experiences and outcomes.

2.4 Learning in Online Environments

Digitalization enables flexible access to learning content and interactive elements that enhance understanding. Studies show that interaction and engagement are key factors for learning success, whereas the course format itself *has no influence on actual learning success* ("keinen Einfluss [...] auf den tatsächlichen Lernerfolg hat" (Klug & Seethaler, 2021, 1f)). Therefore, maximizing learning opportunities is crucial. In full-day online courses, maintaining variety and motivation is particularly important (Ketter et al., 2022).

Successful online mentoring requires openness to technology-supported communication and can even accelerate collaboration processes (Baumann, 2022, p. 356);(Chrobak, 2004, p. 58).

2.5 Self-Directed Learning in Online Courses

Even before the pandemic-driven transition in 2019, self-directed learning was extensively studied. Sharples describes learning as a continuous process of negotiation and exploration (Sharples, 2005, p. 6). Students who employ effective self-learning strategies achieve better results in online courses, emphasizing the importance of learning strategies and time management.

A high sense of self-efficacy promotes the use of self-learning strategies, which can be further supported by digital platforms (Pelikan et al., 2021, p. 394), (Baumann, 2022, p. 102). Context management and accompanying support are crucial success factors (Lödermann, 2024, p. 80).

2.6 Factors Influencing Learning Success

Examinations are primarily identified as a factor that significantly influences student learning success

(Heinzel et al., 2020, p. 43). In addition, external conditions that cannot be influenced by instructors, such as proximity to home, individual time frames, and peer networking (see above), also play an important role. Hussner et al., like Koegler et al., demonstrated that the perceived workload of online teaching, compared to regular teaching, has increased (Hußner et al., 2022), and that *students' stress perception* is high (Besa et al., 2022, p. 7), while at the same time, time- and location-independent learning in online courses allows for greater individualization compared to face-to-face courses (Kossack & Bender, 2022, p. 9).

The arrangement and function of online units, as well as the type of online tools used, can also influence learning success. Here, the specific function of each unit is crucial, particularly whether it serves as a mere replacement for face-to-face teaching or as an independent learning unit (Towfigh et al., 2022, p. 18).

2.7 Task Taxonomies

To compare the learning success of different task formats, the impact of various teaching methods must be considered. Learning success can only be assessed based on content that has been explicitly taught according to *Constructive Alignment*. It is therefore necessary to demonstrate that the required competencies for exam tasks could have been acquired. The use of digital teaching methods depends on factors such as the number of sessions, didactic design, and curricular integration (Lerner & Luiz, 2019).

In scientific and technical disciplines, performance assessment through various task types is essential. Taxonomies such as SOLO, Anderson & Krathwohl's revision of Bloom's Taxonomy, and Webb's Depth of Knowledge (DOK) classify cognitive demands in teaching and learning processes. All models require extensive knowledge of the underlying literature (Biggs & Tang, 2011, p. 47).

Type 1: Repetition Tasks. Aiming to consolidate basic knowledge and routine skills, these tasks range from unistructural to multistructural requirements according to the SOLO taxonomy. Anderson & Krathwohl assign them to the lower levels of the cognitive process dimension, "remember" and "understand" (Wilson, 2016, p. 2). In the knowledge dimension, they correspond to "Factual Knowledge" (Krathwohl, 2002, 215ff).

Type 2: Analysis Tasks. Requiring the application of concepts for problem-solving, these tasks range from multistructural to relational requirements. According to SOLO, they promote relational understanding by recognizing and utilizing relationships between concepts. Anderson & Krathwohl classify them at the higher levels "Apply" and "Analyze" (Bay, 2018; Krathwohl, 2002).

Type 3: Synthesis Tasks. Requiring deep understanding and the ability to apply knowledge in new contexts, these tasks reach a relational to extended abstract level according to SOLO. They correspond to the highest stages in Anderson & Krathwohl's taxonomy ("Evaluate" and "Create") and the top levels of Webb's DOK, which involve critical thinking, planning, and project development (Krathwohl, 2002, p. 215).

3 RESEARCH DESIGN

This chapter outlines the general approach to investigating the relationship between online participation/engagement and conceptual expertise in the context of a course module on real-time media networks. The aim is to gain specific insights into how students' online presence influences their ability to handle complex conceptual, analytical, and creative tasks.

3.1 Research Question, Hypotheses

This paper examines the following question, which is differentiated into three hypotheses listed in Table 1:

> "Does the performance of students in solving complex conceptual and synthesis tasks increase disproportionately compared to simpler repetition and calculation tasks with the online attendance time in courses conducted entirely online in a technical module? "

3.2 Methods

Structured Content Delivery. Learners gain an adequate understanding of the module content through interactive teaching methods and appropriate content delivery.

Logical Sequence and Traceability of Content. As part of the module, students are actively involved, and targeted questions and discussion prompts are used to foster critical reflection on the topic.

Appropriate Taxonomy. A suitable taxonomy is chosen to classify learning objectives and tasks for assessing the difficulty level.

Topic-Focused Days. Allow for in-depth exploration of specific topics and improve the structuring of the learning process. Each block focuses on a specific topic.

Increasing Complexity Levels by Demand Areas within each cohesive session block. Knowledge transfer progresses through application, analysis, and evaluation to support the learning process in a targeted and documentable manner.

Interactive Competency Development through the use of teaching methods that not only promote knowledge acquisition but also build on analysis and evaluation to support the development of synthesis skills.

Taxonomy. For this study, Anderson and Krathwohl's *Revision of Bloom's Taxonomy* was selected as the most suitable classification (Krathwohl, 2002). It covers a broad cognitive spectrum and enables precise learning objectives. In Table 3 , the exam tasks are assigned to the corresponding primary and sublevels of the competency dimensions.

3.3 Data Collection

A quantitative approach was used for data collection. The online attendance times of students were pseudonymized to assign participation to the different topic areas. Additionally, the examination results were divided into the three named cognitive requirements (see Task detailiation in Table 3) and recorded in points. Individual scores from eight tasks were collected for the examination.

Table 1: Hypotheses, each formulated as a null hypothesis (H_0) and corresponding alternative hypothesis (H_1).

H_A	$H_{A,0}$	There is no positive correlation between attendance time and performance in complex concept tasks.
	$H_{A,1}$	The correlation between attendance time and performance in complex concept tasks 3 is positive.
H_B	$H_{B,0}$	The correlation between attendance time and performance in complex concept tasks 3 is not greater than for task type 1.
	$H_{B,1}$	The correlation between attendance time and performance in complex concept tasks 3 is greater than the corresponding correlation for task type 1.
H_C	$H_{C,0}$	The correlation between attendance time and performance in complex concept tasks 3 is not greater than for task type 2.
	$H_{C,1}$	The correlation between attendance time and performance in complex concept tasks 3 is greater than the corresponding correlation for task type 2.

4 IMPLEMENTATION OF THE MODULE

4.1 Module Concept

The courses primarily aimed to provide students with a deep understanding of the content (**Student Learning First**) and were structured in time-blocked units according to knowledge and taxonomy levels for this study.

The seven full-day online sessions were structured so that each topic area was assigned a clearly defined time block, with increasing complexity throughout. The goal was a coherent learning experience that actively engaged students, promoted critical thinking, and established a measurable link between knowledge levels and process dimensions. Interactive methods supported not only knowledge acquisition but also the development of analytical, evaluative, and synthesis skills through discussions and practical applications to tackle complex tasks.

4.2 Courses

Learning settings with "challenging tasks and exercises throughout the learning process" enable needs-based knowledge acquisition (Erpenbeck et al., 2015, p. 1). Since prior knowledge is a key factor for learning success (Hurzlmeier et al., 2024, 108ff), courses and materials were designed adaptively to "mitigate" differences in prior knowledge (Hurzlmeier et al., 2024, p. 111). The structure followed Anderson & Krathwohl's taxonomy, and digital materials were specifically selected to enhance self-efficacy by activating self-learning strategies (Pelikan et al., 2021).

The individual sessions are listed in Table 2 . The module begins with an introductory session and concludes with exam preparation. The content-relevant sessions are aligned with the exam tasks. Table 2 divides the first four days into "morning" and "afternoon" sections, in which the topics of the exam tasks were comprehensively covered. Subsequent sessions only included brief reviews to avoid redundancy.

Each topic block started with an introduction, with complexity systematically increasing throughout the session.

Table 2: Courses and assigned examination tasks.

Period		Topic	Task Description	Task Type
Day 1 morn.	**00**	Introduction	—	—
aftern.	**01**	Sounds and Digitalization	Task 2 - Metadata in AES-3 protocol	1 - Remember, Understand
Day 2 morn.	**02**	Audio Transmission	Task 4 - Audio file analysis	1 - Remember, Understand
aftern.	**03a**	Basics of Networking: Review of OSI Model, Ethernet, Protocols	Task 1 - Layer addressing	1 - Remember, Understand
Day 3 morn.	**03b**	Basics of Networking starting from "Packets in Detail"	Task 3 - Assemble sample data into an IP packet	2 - Analyze, Apply
aftern.	**03**	Basics of Networking: Audio over Ethernet vs. over IP	—	—
Day 4 morn.	**04**	Network Analysis with Wireshark, Switch Knowledge	Task 5 - Virtual switch shopping	2 - Analyze, Apply
aftern.	**05**	Audio over IP sentiment analysis + final task	Task 6 - Spanning Tree Protocol	1 - Remember, Understand
Day 5 morn.	**06**	Sentiment analysis evaluation, AoIP components: PTP	Task 7 - Precision Time Protocol	2 - Analyze, Apply
Day 6	**07**	Network setup using Dante - Spanning Tree - IGMP snooping	Task 8 - Redundancy in Dante networks: design with sketch and explanation	3 - Evaluate, Create
Day 7	**08**	Exam preparation	—	—

4.2.1 Interactive Tools

To address in-depth questions that allow connecting facts initially not perceived as related, collaborative maps were used as a central tool. Students worked both collaboratively and individually on interactive maps that visually represented individual facts or entire structures as large-scale maps with links (Cross, 2023, p. 88). Additionally, expandable digital posters were provided, detailing the composition of network packets across all layers (Ethernet, IP, ...) with typical variations and exceptions. Figure 2 illustrates some of the interactive tools used. Furthermore, comprehensive sheets with overviews of specific encoding variants were introduced. Consistent use of these tools was intended to foster insights into commonalities and fundamental, recurring principles, even when the underlying procedures initially appeared very different.

Additionally, experiential learning was supported through "hands-on" activities that enabled individual progress, particularly in analysis and synthesis skills: networks could be analyzed "live", and content could be decoded. All tools presented and used live relied exclusively on freely available software, such as "Wireshark" for network analysis (Hein et al., 2021), "Cisco Packet Tracer", a cross-platform visual simulation tool for creating and analyzing network topologies, or "FFmpeg" for encoding/decoding and analyzing audio material (Chappel, 2018; Riselvato, 2020). The use of exclusively freely accessible tools allowed for individual (continued) engagement to any extent. Adams et al. describe such "hands-on" activities as "just-in-time support" and advocate for these measures to classify learning strategies into their highest postulated Level 4 (Adams et al., 2010, p. 6).

Both the exploration of visual maps and the "playing" with analysis and simulation tools enabled a connected knowledge development through sufficient engagement of students in the group and individual follow-up (Blackwell, 2001, p. 10) or "active knowledge construction" (Graham, 2006, p. 31). Sequences of actions were visually experienced, and a subsequent concept could be assembled along these cognitively targeted sequences (Romero-Tejedor, 2021, p. 68). Both served as a foundation for system development in the comprehensive synthesis task of the exam. The courses were subjectively deemed sufficiently suitable to support self-learning, motivate students, and prepare them for the synthesis tasks (Type 3: Synthesis Tasks).

4.3 Development of Exam Tasks

The exam tasks were based on the taxonomy selected in Section 3.2 , which follows Anderson and Krathwohl's revision of Bloom's Taxonomy. This taxonomy was divided into 3 blocks: *Repetition* (1), *Analysis* (2), and *Synthesis* (3), upon which the tasks were subsequently developed. The tasks were designed to contain typical characteristics of the respective taxonomic category and are detailed in Table 3.

"Open-Everything" Exam. The assessment was designed as an "Open-Everything" exam (Jagoe, 2014; Wieman, 2017). "Open-Everything" represents an extension of "Open-Book" formats: In "Open-Everything" exams, all resources, including the use of the Internet, were explicitly allowed. The only prohibition was contacting other individuals, either physically or online. The "Open-Book" format—or its extended "Open-Everything" version—reduces students' concerns about failure anxiety and leads to lower exam tension (Michael et al., 2019, p. 179) and less stress (Afshin Gharib et al., 2012, p. 476). Moreover, this format aligns more closely with real-world work environments, where all resources are available

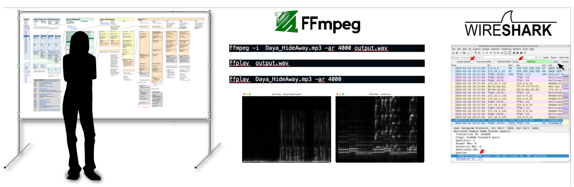

Figure 2: Interactive tools.

Table 3: Classification of examination tasks according to Anderson and Krathwohl's revision of Bloom's taxonomy with the classification into "Knowledge Dimension" and "Cognitive Process Dimension" (Krathwohl, 2002, 214 f.).

	Task Description	Knowledge Dimension X. Level Xx: Sublevel	Cognitive Process Dimension	Category
1	Layer addressing	A. Factual Knowledge Aa: Knowledge of terminology	1.0 Remember 1.1 Recognizing	Type 1: Remembering Tasks
2	Metadata in serial AES-3 protocol	A. Factual Knowledge Ab: Knowledge of specific details and elements	2.0 Understand 2.2 Exemplifying	Type 1: Remembering Tasks
3	Assemble sample data into IP packet	C. Procedural Knowledge Ca: Knowledge of subject-specific skills and algorithms	3.0 Apply 3.1 Executing	Type 2: Analyzing Tasks
4	Audio file analysis	B. Conceptual Knowledge Ba: Knowledge of classifications and categories	2.0 Understand 2.7 Explaining	Type 1: Remembering Tasks
5	Virtual switch shopping	C. Procedural Knowledge Cb: Knowledge of subject-specific techniques and methods	3.0 Apply 3.2 Implementing	Type 2: Analyzing Tasks
6	Spanning Tree Protocol	B. Conceptual Knowledge Bb. Knowledge of principles and generalizations	4.0 Analyze 4.3 Attributing	Type 1: Remembering Tasks
7	Precision Time Protocol	C. Procedural Knowledge Cb. Knowledge of subject-specific techniques	5.0 Evaluate 5.1 Checking	Type 2: Analyzing Tasks
8	Redundancy: design with sketch and explanation	C. Procedural Knowledge Cc. Knowledge of criteria for determining when to use appropriate procedures	6.0 Create 6.2 Planning	Type 3: Evaluating Tasks

for problem-solving (Parker et al., 2021, p. 5). According to Senkova et al., the exam format ("Closed" or "Open") plays a role in allowing test questions in "Open" formats to be designed more deeply, eliciting elaborative thought processes (Senkova et al., 2018, p. 22), which is a prerequisite for successfully solving the Type-3 question.

Tasks of Type 1 comprised four tasks with fundamental cognitive requirements, focusing on the recall and reproduction of essential content. The level of difficulty was designed so that the relevant content could be understood through active listening in the lectures. Figure 3 provides an example task.

The content of the Type 1 tasks was intentionally

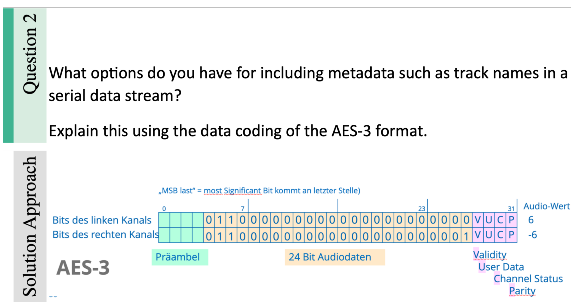

Figure 3: Example question for Type 1: Repetition Tasks (The illustration is partly labeled in German, as this is a German exam. The question texts were translated for this paper).

only briefly addressed during the exam preparation, as the content could be directly extracted "1:1" from the provided materials. This ensured that the evaluation would not be biased by allowing mere participation in the exam preparation to be entirely sufficient. The achievable score for these tasks accounted for 40 % of the total points.

Tasks of Type 2. This task type required deeper cognitive processing and consisted of three tasks, collectively accounting for 40 % of the total achievable score. Combined with the Type 1 tasks, this allowed for 80 % of the total score to be attained. The key difference from Type 1 was the necessity to identify relationships between previously isolated topics and develop a cohesive understanding. Figure 4 illustrates this using the example of network packet assembly. Each task consisted of two parts:

1. **Fact Extraction:** Students were required to gather relevant facts from different sources and correctly name them. This part documented their ability to systematically retrieve information and ensured that a minimum score could be achieved to pass the exam.
2. **Application and Calculations:** Using the collected information, students had to perform calculations to reinforce their understanding of the relationships.

Tasks of Type 3 corresponded to the highest levels of cognitive requirements, as described in Section 2.7 . It presented students with complex challenges requiring deep understanding, the integration of different knowledge domains, and creative problem-solving skills. The respective task accounted for 20 % of the total achievable points.

To successfully complete this task, practiced use of interactive tools was required. The necessary thought processes were *generically developed* during the corresponding session through structured discussion. The goal was to enable students to apply their knowledge to real-world scenarios and, based on these considerations, design a functional system.

The assigned task is described in Figure 5. Students were required to design a redundant setup for a real-time network for audio transmission. Additionally, they had to create a sketch and provide a detailed explanation of the chosen architecture. This task not only assessed their procedural knowledge of network technologies but also their ability to make creative and strategic decisions, develop an optimal solution, and substantiate it with arguments.

4.4 Evaluation Plan

The session days were divided into thematic complexes, and the evaluation was conducted based on the exam tasks, each of which was clearly assigned to a thematic complex. Initially, basic statistics were calculated, including average results per thematic complex and attendance times in the sessions. Subsequently, tasks were grouped by task type to test the hypotheses from Section 3.1.

Correlations WITHIN Task Types. For each of the three task types, the correlation of normalized exam results with attendance classes was calculated. Since attendance classes were ordinally scaled, Spearman's rank correlation was used (Bortz & Schuster, 2010, p. 388). The first vector represented the rank of the attendance class, while the second vector depicted the relative score as a percentage of the achievable points (metric scale level). Since no missing values occurred in either vector, the application of a "NaN-Policy" was unnecessary.

Fisher Z-Transformation. To ensure comparability of the correlation coefficients across task types (Behnke & Behnke, 2006, p. 264), Fisher's Z-transformation was applied (Tachtsoglou & König, 2017, p. 124). This transformation converts the distribution of correlation coefficients into an approximately normal form, allowing for the calculation of confidence intervals and coefficient comparisons (Bortz & Schuster, 2010, p. 156).

The Spearman correlation coefficients r_1 through r_3 were transformed to Z_1, Z_2, and Z_3 as follows:

$$Z_i = \frac{1}{2}\ln\left(\frac{1+r_i}{1-r_i}\right)$$

Confidence Intervals. The variance of the Z-values is defined as $s_i = \frac{1}{n_i-3}$, where n is the number of observations. Accordingly, the standard deviation is $\sigma_i = \frac{1}{\sqrt{n_i-3}}$ (Rasch et al., 2014, p. 89).

The 95% and 99% confidence intervals for Z_i are given by (Bortz & Schuster, 2010, p. 589):

$$CI_{95} = Z_i \pm 1.96 \cdot \frac{1}{\sqrt{n_i-3}}, \quad CI_{99} = Z_i \pm 2.576 \cdot \frac{1}{\sqrt{n_i-3}}$$

The boundaries of these confidence intervals were back-transformed to obtain the corresponding intervals for r_i: $r = \frac{e^{2Z}-1}{e^{2Z}+1}$

Comparison of Correlation Coefficients ("BETWEEN"). To determine the difference between two correlation coefficients, Fisher's Z-transformation was also used to standardize the correlations, stabilize their dispersion, and make the difference interpretable as an effect size measure (Rasch et al., 2014, p. 90).

To calculate the statistical confidence of the difference between two correlation coefficients, the Z-value for the difference of the coefficients was computed. For two correlation coefficients r_1 and r_2 with corresponding transformed values Z_1 and Z_2, and with the respective Z-space variance $\sigma^2 = \frac{1}{n-3}$, the critical Z-value for the difference was calculated, assuming

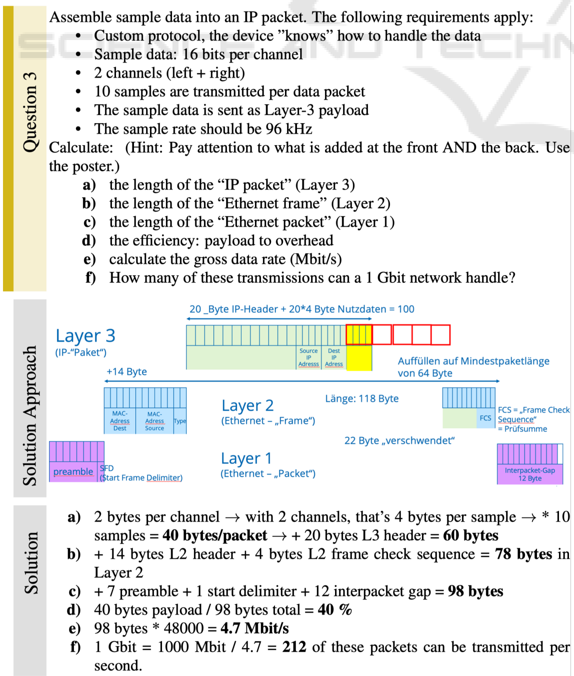

Figure 4: Example question for Type 2: Analysis Tasks (The illustration is partly labeled in German, as this is a German exam. The question texts were translated for this paper).

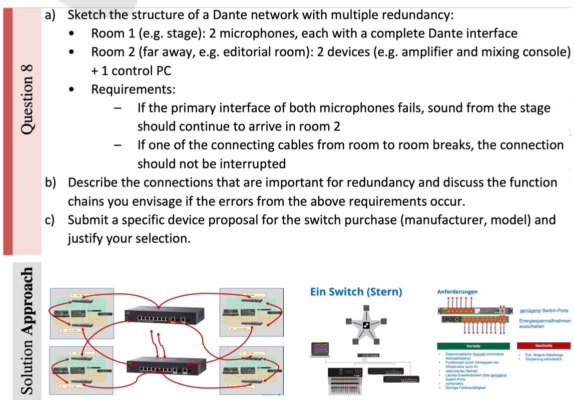

Figure 5: Example question for Type 3: Synthesis Tasks (The illustration is partly labeled in German, as this is a German exam. The question texts were translated for this paper).

variances add up $\left(\frac{1}{n_1-3}+\frac{1}{n_2-3}\right)$, as:

$$Z_{\text{diff}} = \frac{Z_1 - Z_2}{\sigma} \quad \text{where} \quad \sigma = \sqrt{\frac{1}{n_1-3}+\frac{1}{n_2-3}}$$

Z_{diff} thus represented the mean distance of the difference in multiples of the standard deviation. This Z_{diff} could then be used to determine the statistical power of the difference between the correlation coefficients. A Z-value greater than 1,64 (one-sided test at the $\alpha = 5\%$ level) or 2,33 (one-sided test at $\alpha = 1\%$ level) indicates a significant positive difference between the correlation coefficients.

5 RESULTS

The courses described in Section 4.2 were conducted entirely online in block format over one semester.

A total of 30 students were enrolled in the module. Of these, 22 registered for the exam, 3 non-registered students participated partially in the sessions, and 5 did not attend any session. The cohort under investigation consisted exclusively of the 22 students who participated in the exams.

5.1 Methodological Outlier

One participant reported at the beginning of the module that they regularly install real-time networks in their current work and were therefore already very familiar with all the content. The participant announced that they would only attend sporadically to see if any unfamiliar topics were discussed. This individual, classified as a *methodological outlier* due to their extensive prior knowledge, was excluded from the analysis. However, in diagrams showing all data, the data for this *methodological outlier* are displayed but marked separately. This outlier was excluded from the calculation of statistical measures.

5.2 Sessions

The sessions were divided into thematic sections, as described in Section 4.2 (“Courses”) , which were clearly assignable to the completed exam tasks. The assignments are detailed in Table 2 , and Table 3 lists all exam tasks with their assignment to the task types described in Section 2.7 based on the taxonomy outlined in Section 3.2 .

5.3 Attendance

Attendance at the individual sessions was heterogeneous. Since the sessions, as described in Section 4.2 (“Courses”) , began with an introduction and increased in complexity over time, precise attendance minutes cannot be directly assigned and compared between sessions. Therefore, attendance per session was normalized to 0 % to 100 %, and the normalized values were divided into the following 4 ordinal equidistant classes (“binning”):

- <25 %
- 25 % to 50 %
- 50 % to 75 %
- >75 %

Figure 6 graphically shows the resulting classification in the diagram on the right. The same colors are consistently used for the 3 task types and attendance classes in all diagrams, see Figure 6 .

5.4 Exam Results

The achieved success rates, as shown in the left diagram of Figure 6, reveal an average success rate of over 90 % in half of the tasks, with all Type 1 tasks (Type 1: Repetition Tasks) except for Task 2 showing success rates above 80 %. Task 2 exhibits very high variance, with results ranging from 0 % to 100 % and a standard deviation of 31 %.

Tasks of Type Type 2: Analysis Tasks , an example of which is shown in Figure 4 , exhibit decreasing success rates: from an average of 99 % in Task 3 to 91 % in Task 5 and 77 % in Task 7.

The task of Type Type 3: Synthesis Tasks , fully presented in Figure 5 , shows an average success rate of 70 % (“Task 8” in Figure 6).

The averaged success rates, as shown in Figure 7 , indicate a range of 12 % (88 % to 100 %) for Task Type 1 across all attendance classes and a range of 9 % (76 % to 85 %) for Task Type 2.

The averaged success rates for Task Type 3 show a range of 57 % (35 % to 92 %), increasing with higher attendance classes.

5.5 Correlations WITHIN Task Types

The Spearman correlation coefficients for Task Types 1 to 3 are $r_1 = 0.14$, $r_2 = 0.27$, and $r_3 = 0.85$. The transformed Z-values and calculated confidence intervals indicate that the correlation coefficients differ. The correlation coefficients increase with the level of task difficulty: $r_1 < r_2 < r_3$.

Figure 1 graphically and numerically presents the calculated confidence intervals for the correlation coefficients. The regression lines shown in Figure 8 visually match upon inspection.

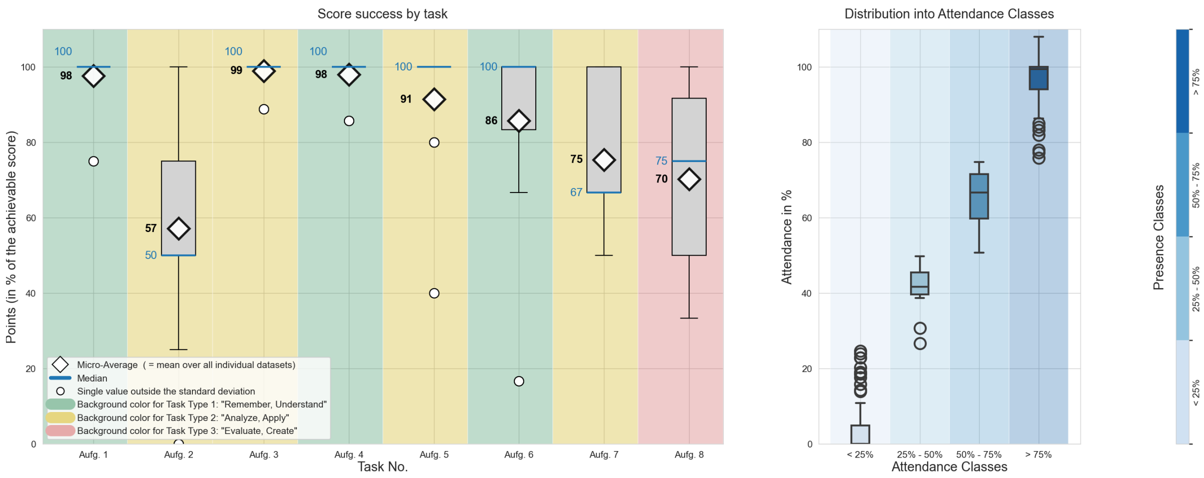

Figure 6: Overview of Attendance.
Left: Distribution of relative success rates by task; The task type colors match those throughout the document; They have been slightly lightened due to the large areas (see legend).
Right: Frequency of attendance across ordinal attendance classes. Attendance percentages on the metric scale exceed 100 % in some cases because participants stayed after sessions to clarify questions (see explanation in the text under "Attendance").

5.6 Comparison of Correlation Coefficients (BETWEEN)

When comparing the confidence intervals of the coefficients for the 3 task types, Figure 1 shows that the intervals $CI_{95,1}$ and $CI_{95,2}$ for Task Types 1 and 2 overlap significantly. The interval $CI_{95,3}$ for Task Type 3 does not overlap with the other intervals, neither in the 95 % confidence interval nor in the 99 % confidence interval.

The distances between the confidence intervals of the 3 task types (correlations BETWEEN task types) in Z-space are:

$Z_{\text{diff}} = 0.77$ for the comparison of r_1 and r_2

$Z_{\text{diff}} = 4.25$ for the comparison of r_1 and r_3

$Z_{\text{diff}} = 3.64$ for the comparison of r_2 and r_3

Thus, the difference in correlation coefficients is:

- $\mathbf{Z_{\text{diff},2-1} = 0.77}$ ($p = 0.2219$). The difference in correlation coefficients is 0,77 standard deviations in Z-space with strongly overlapping confidence intervals.
- $\mathbf{Z_{\text{diff},3-1} = 4.25}$ ($p = 0.0000$). The difference in correlation coefficients is 4,25 standard deviations in Z-space with no overlap in the 99 % confidence interval.
- $\mathbf{Z_{\text{diff},3-2} = 3.64}$ ($p = 0.0001$). The difference in correlation coefficients is 4,25 standard deviations in Z-space with no overlap in the 99 % confidence interval.

6 ADDRESSING THE RESEARCH QUESTION

The research question formulated in "Research Question, Hypotheses" is examined below using the hypotheses H_A, H_B, and H_C based on the results.

6.1 Analysis of the Hypotheses

Hypothesis H_A. The correlation between attendance and exam success for Task Type 3 (Type 3: Synthesis Tasks) shows a very strong positive relationship with $r = 0.85$ and a 99 % confidence interval of $CI_{99\%} = [0.57, 0.95]$ (Field et al., 2012, p. 93).

⇒ The hypothesis $H_{A,0}$ (" There is no positive correlation between attendance time and performance in complex concept tasks 3. ") can thus be rejected at the $CI_{99\%}$ confidence level.

Hypothesis H_B. The positive difference between the correlation coefficients r_3 (Type 3: Synthesis Tasks) and r_1 (Type 1: Repetition Tasks) was observed outside a 99,9 % acceptance range from $H_{A,0}$ with $p = 0.0000$, indicating that the correlation coefficient r_3 is significantly greater than r_1 ((Cohen, 1988)).

⇒ The hypothesis $H_{B,0}$ (" The correlation between attendance time and performance in complex concept tasks is not greater than for task type 1. ") can be falsified.

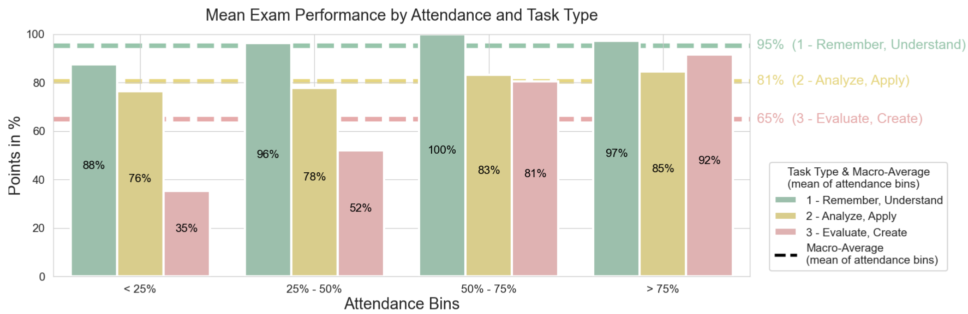

Figure 7: Average success rates by task type and attendance.

Hypothesis H_C. The positive difference between the correlation coefficients r_3 (Type 3: Synthesis Tasks) and r_2 (Type 2: Analysis Tasks) was observed outside a 99,9 % acceptance range from $H_{C,0}$ with $p = 0.0001$. This indicates that the correlation coefficient r_3 is significantly greater than r_2 ((Cohen, 1988)).

⇒ The hypothesis $H_{C,0}$ (" The correlation between attendance time and performance in complex concept tasks is not greater than for task type 2. ") can be falsified: r_3 is significantly greater than r_1 within the scope of this study.

6.2 Answering the Research Question

The study results show that student performance in solving complex conceptual and synthesis tasks (Type 3) in the investigated course module significantly correlates with online attendance time.

⇒ $H_{A,1}$ (" The correlation between attendance time and performance in complex concept tasks 3 is positive. ") .

This correlation is significantly higher compared to repetition tasks and also significantly higher compared to analysis and calculation tasks.

⇒ $H_{B,1}$ (" The correlation between attendance time and performance in complex concept tasks is greater than for task type 1. ")

⇒ $H_{C,1}$ (" The correlation between attendance time and performance in complex concept tasks is greater than for task type 2. ")

7 DISCUSSION

The exam results showed that students consistently achieved high success rates in Type 1 tasks (Type 1: Repetition Tasks), except for Task 2, which exhibited very high variance. This could indicate differences in individual preparation and varying levels of understanding of fundamental concepts. Another plausible explanation is the relatively higher difficulty level of Task 2 (Table 3) compared to the other Type 2 tasks (Type 2: Analysis Tasks). Task 2 is detailed in Figure 3 ("Example question for Type 1: Repetition Tasks (The illustration is partly labeled in German, as this is a German exam. The question texts were translated for this paper)") ; the subject-matter reader may form their own judgment.

7.1 Correlations Within Task Types

For Type 2 tasks (Type 2: Analysis Tasks), a stronger relationship between attendance and success was observed. The correlation coefficient $r_2 = 0.27$ is higher than that of Task Type 1 with $r_1 = 0.14$, indicating a general trend. However, the confidence intervals $CI_{95,1}$ and $CI_{95,2}$ both include the value 0, meaning the correlation coefficients r_1 and r_2 do not show a significant positive increase.

In this study, a very strong relationship between attendance and exam success in complex tasks was observed. This confirms the alternative hypotheses $H_{A,1}$ (" The correlation between attendance time and performance in complex concept tasks 3 is positive. ") . It should be noted that a strong correlation does not imply causation.

The correlations between attendance time and scores across the different task types showed that higher attendance is associated with better performance, particularly in more complex tasks.

7.2 Comparison of Correlation Coefficients

The relationship between attendance time and exam success, measured as scores achieved, is significantly higher for complex tasks 3 compared to repetition or calculation tasks (1 and 2). This confirms the alternative hypotheses $H_{B,1}$ and $H_{C,1}$.

In the respective parts of the courses, less direct instruction was provided, and more development and discussion occurred. Numerous solution proposals

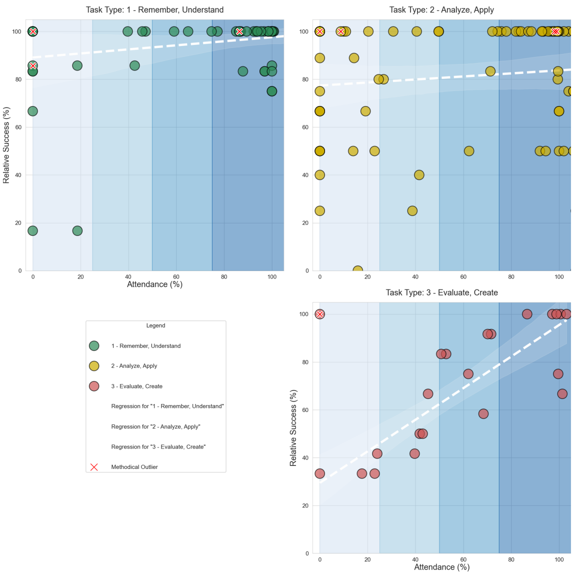

Figure 8: All individual tasks separated by task type. The attendance classes are desaturated in the background for orientation. A regression line (excluding the methodological outlier) was added for visual verification.

were presented, which, during plenary discussions, often led to insights within the student group without any intervention or comments from the instructor.

Additionally, it was observed that students who participated in the development-oriented discussion rounds were able to develop innovative solutions and creative problem-solving strategies for the complex task. This suggests that the interactive and collaborative nature of these sessions significantly enhanced students' critical thinking and problem-solving skills.

These immediate peer-derived insights appear to embed themselves significantly deeper in process and synthesis memory than mere listening.

Students who voluntarily chose not to participate in these sessions consistently performed worse. While learning strategies for repetitive knowledge appear relatively egalitarian, developmental and synthesis skills seem to be better acquired through group discussions or individual, in-depth engagement with interactive tools, such as work posters or simulation software provided during the courses.

7.3 Outlook and Future Work

Beyond the approach of the present study, the results highlight the importance of active participation and engagement in collaborative learning environments to develop the higher cognitive skills essential for success in demanding technical disciplines. These findings can serve as a basis for future design and optimization of teaching methods to further enhance learning outcomes in digital educational formats.

Further research could focus on differentiating this study further into specific teaching methods to examine their impact on engagement and learning outcomes.

Involving students and comparing the results with their internal perspectives would be another approach to differentiation, as well as further studies in the professional field and exploring which content and implementation methods are deemed suitable by students in retrospect.

8 SUMMARY

The literature indicates a fundamental relationship between participation in online courses and learning success. This study demonstrated that students who actively and regularly participated in online sessions achieved significantly better results in synthesis-based, cognitively demanding tasks. This supports the argument that increased participation in online courses has a significantly positive impact on the ability to solve complex tasks.

In summary, the findings of this study underline the importance of online presence for learning success in technical modules. Particularly for tasks requiring higher cognitive abilities, active participation in online courses appears to be crucial for success.

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