

Camera-Based AI in German Classrooms: The State of Evidence

Research Unit

July 2026

1 Introduction

AI is increasingly used in education through camera-based systems that serve three distinct purposes: exam proctoring, behaviour and attendance monitoring, and classroom management. In this paper, exam proctoring refers specifically to in-class camera-based monitoring, meaning cameras installed in the physical classroom that observe the exam room rather than the remote, computer-based proctoring common in online testing (e.g., webcam lockdown browsers used for take-home or remote exams). These systems verify identity and detect irregular behaviour, such as unauthorised movement or communication between students, during in-person assessments. Behaviour and attendance monitoring tracks student presence, engagement, or conduct during regular instruction, often feeding attentiveness data back to teachers. Classroom management, in this narrower sense, refers to camera-based AI applications that support the day-to-day administrative and organisational running of a class. Typical functions include automated attendance-taking via facial recognition at the start of a session, headcount verification and seating-arrangement tracking.

China provides public examples of how these systems can be used in practice. During the 2025 Gaokao, China's national college entrance exam, China Daily reported that some exam rooms used real-time intelligent surveillance systems to flag irregular behaviour, including whispers, frequent glances between students, and inattentive proctors [1]. This is an example of in-class proctoring. In another example, Reuters reported that Hangzhou No. 11 Middle School installed a smart classroom behaviour-management system developed by Hikvision. The system used cameras and facial-recognition tools to capture students' expressions and movements, detect behaviours such as reading, listening, or sleeping, and provide attentiveness information to teachers [2]. This is an example of behaviour and engagement monitoring during regular instruction.

A third example concerns attendance management. In Paraná, Brazil, facial-recognition software was deployed across more than 1,700 public schools to automate student attendance, replacing traditional roll call with image-based identification [9]. Public-interest groups later reported legal challenges concerning the use of facial recognition to record attendance [10]. The case combines a practical classroom-management function with significant privacy and governance concerns.

This white paper asks whether similar early-adoption signals can be found in Germany. The evidence reviewed here does not show broad, publicly documented deployment of AI-based classroom monitoring systems in German schools. The stronger pattern is controlled experimentation: university-led research, classroom-video studies, eye-tracking projects, and learning-support tools developed under research conditions.

German adoption also has to be assessed state by state. School education is primarily governed by the Länder, so legal conditions, procurement channels, and implementation timelines can differ across Germany. Bavaria is especially relevant in 2026. On 22 July 2026, the Bavarian Landtag adopted, with amendments, a school-law bill whose published materials included digitally supported

assessments and the processing of image and audio recordings [12, 13]. Because the consolidated enacted wording was not yet available in the public record reviewed for this paper, institutions should verify the final text and commencement before relying on it. The development is treated as a state-level regulatory signal rather than evidence of deployment or a general authorisation for AI-based classroom monitoring.

Bavaria also provides a demand-side signal for in-class exam supervision. The Bavarian Ministry of Education publishes guidance on AI-assisted cheating in written assessments and describes it as an active challenge for schools [14]. Assessment integrity has therefore entered official state-level discussions, while publicly documented deployment of AI proctoring in German schools remains absent.

Germany is a particularly important case because it combines strong education research with strict expectations around privacy, consent, and data protection. The main question is therefore not simply whether camera-based AI can be used in German education, but under what conditions schools, universities, teachers, students, and regulators may accept these systems.

2 Scope and Methodology

The review covers three evidence areas:

- in-class proctoring, meaning camera-based supervision inside classrooms or exam rooms;
- behaviour and attendance monitoring, including student presence, attention, engagement, and classroom conduct;
- classroom-management support, including administrative and organisational use cases such as attendance-taking, headcount verification, and seating-arrangement tracking.

The evidence was collected from academic papers, university project pages, legal sources, and public institutional guidance. Each source was checked for the technology used, the education setting, and the result or adoption signal it provides.

The paper separates research projects from broad deployment. A classroom study, a university project, and a school-wide commercial rollout are different types of evidence. In Germany, the current evidence is stronger for research and pilot activity than for commercial deployment.

3 Research-Led Classroom AI Evidence

The strongest German evidence comes from classroom AI research rather than school-wide deployment. The studies below focus on teacher attention, student engagement, classroom discourse, and teaching-quality analysis.

3.1 Teacher Visual-Attention Detection

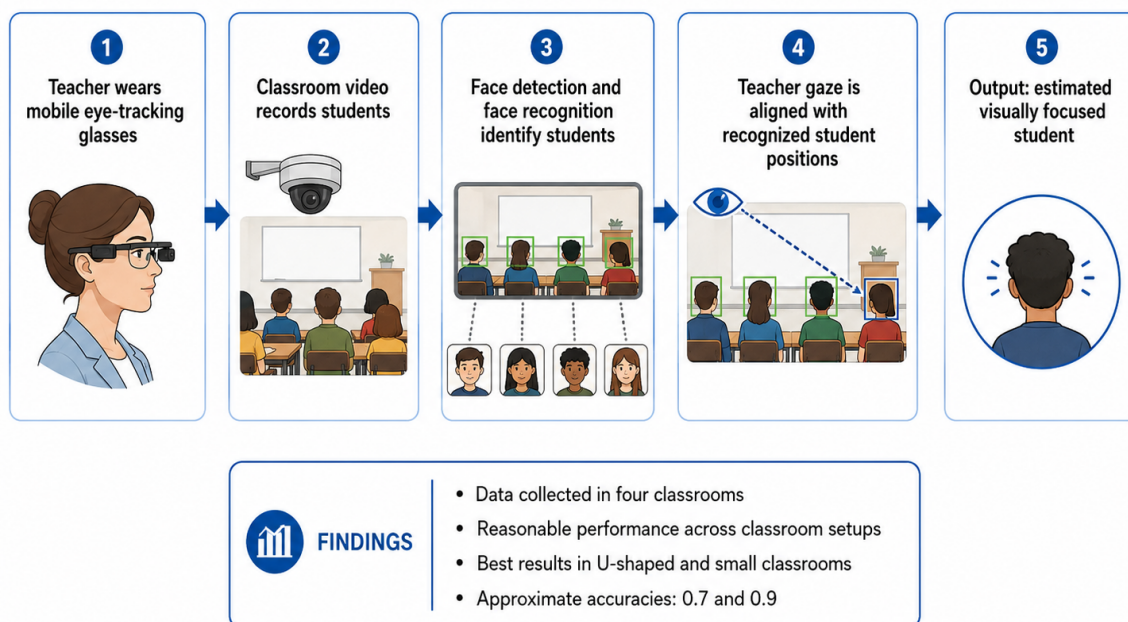
Bozkir et al. (2025) study automated teacher visual-attention detection in real classroom settings [3]. The goal is to estimate which student a teacher is visually focusing on during instruction.

The study combines two data sources. First, teachers wear mobile eye-tracking glasses that record their gaze during mathematics lessons. Second, classroom video is used to detect and recognize students' faces. The system then connects the teacher's gaze with the identified students in the classroom video.

The study involved 4 in-service mathematics teachers and 69 students. It reports that the Bavarian Ministry of Education and Cultural Affairs reviewed and approved the data-protection measures, study design and necessity, and ethical points. Written informed consent was collected from teachers, students, and parents or legal guardians [3].

Automated teacher visual-attention mapping

Based on Bozkir et al. (2025)



Source summary: Bozkir et al., *Automated Visual Attention Detection using Mobile Eye Tracking in Behavioral Classroom Studies* (2025).

Figure 1: Constructor Tech visualization based on Bozkir et al. (2025). The diagram reconstructs the study workflow: mobile eye tracking, classroom video, student-face recognition, teacher gaze mapping, and visual-attention estimation in German classroom settings. This image was generated using artificial intelligence.

The authors report that visually focused students could be estimated with reasonable performance across classroom setups, with stronger results in U-shaped and smaller classrooms. The study validates the technical pipeline rather than measuring an educational intervention outcome. It demonstrates one specifically reviewed, consent-based research study; it does not establish general regulatory approval for camera-based classroom research or commercial deployment.

3.2 Automated Assessment of Encouragement and Warmth

Hou et al. (2024) study whether AI can estimate teacher encouragement and warmth in classrooms [4]. The work uses the German part of the Global Teaching InSights dataset, not a newly conducted classroom experiment. The dataset includes 367 sixteen-minute classroom-video segments from 92 German mathematics lesson recordings.

The method combines classroom video, audio, and transcript-based features to estimate teacher

encouragement and warmth. It also tests GPT-4 on transcript-based scoring. The authors compare the model outputs with human ratings from the classroom-observation protocol.

The results are measurable. GPT-4 and the best trained model reached correlations of $r = .341$ and $r = .441$ with human ratings. An ensemble approach combining both estimates reached $r = .513$, which the authors describe as comparable to human inter-rater reliability [4]. The study shows how classroom recordings can be used for post-hoc teacher-feedback analysis rather than live classroom surveillance.

3.3 Classroom Discourse Quality

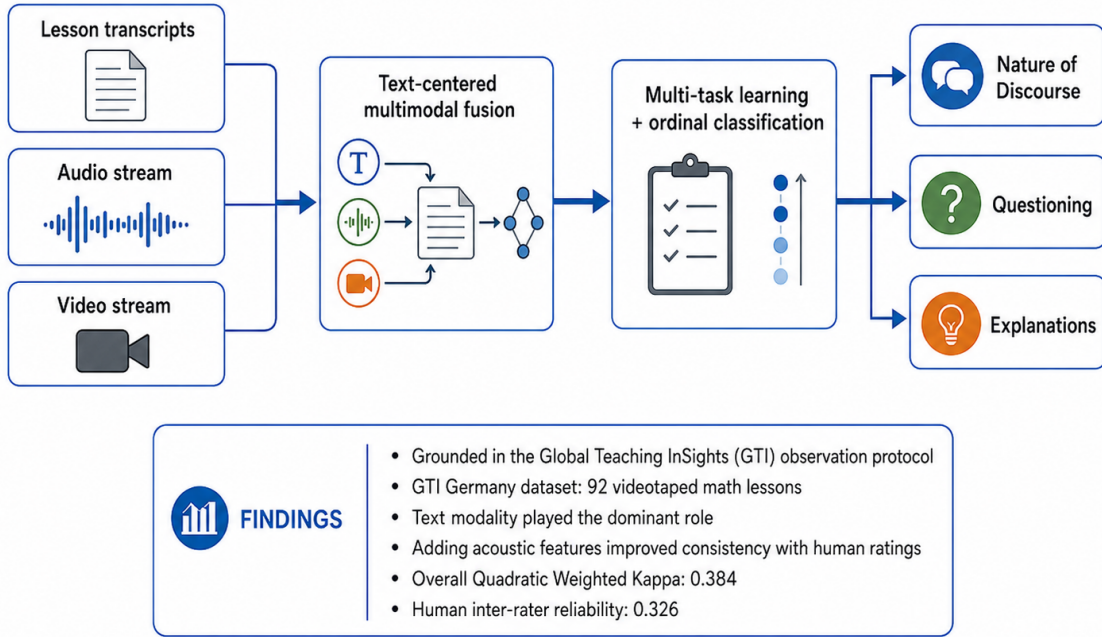
Hou et al. (2025) also use the German classroom-video data from the Global Teaching InSights project [5]. Instead of collecting new classroom recordings, the study analyzes existing lesson videos to assess classroom discourse quality.

The paper focuses on three dimensions from the Global Teaching InSights observation protocol. The first is the nature of discourse, meaning whether classroom talk is mainly teacher-led or whether students actively contribute ideas. The second is questioning, meaning how teachers use questions to guide thinking and check understanding. The third is explanations, meaning how clearly teachers and students develop mathematical ideas during the lesson.

The study mainly uses lesson transcripts, with audio and video added as supporting information. The model predicts ratings for the three discourse dimensions and compares them with human expert ratings [5].

Multimodal assessment of classroom discourse quality

Based on Hou et al. (2025)



Source summary: Hou et al., *Multimodal Assessment of Classroom Discourse Quality* (2025).

Figure 2: Constructor Tech visualization based on Hou et al. (2025). The diagram summarizes the multimodal classroom-discourse-quality pipeline using classroom video, audio, lesson transcripts, extracted features, and model-based scoring of discourse dimensions. This image was generated using artificial intelligence.

The results show that text is the strongest source for this task, while acoustic features improve consistency with human ratings. The model reaches an overall Quadratic Weighted Kappa score of 0.384, compared with human inter-rater reliability of 0.326 [5]. Like the previous GTI-based study, this is post-hoc analysis of existing classroom recordings, not evidence of live classroom deployment.

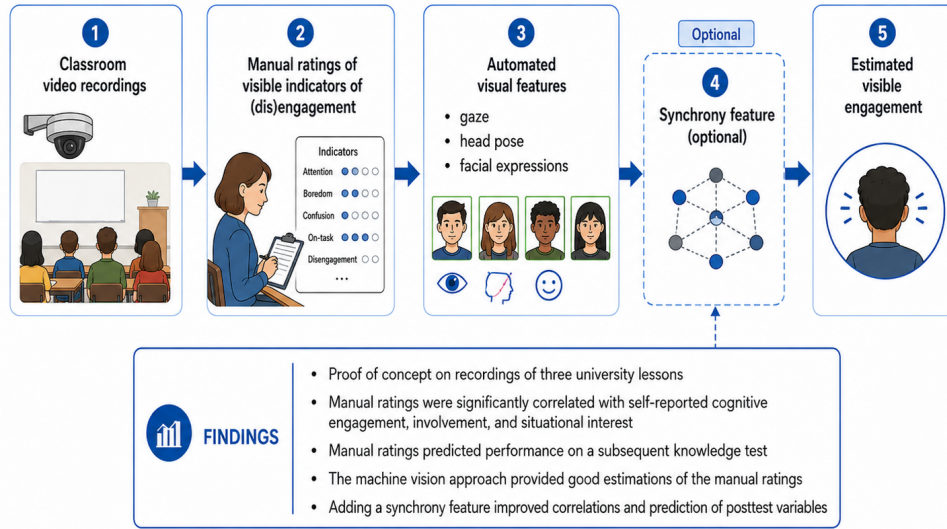
3.4 Visible Student Engagement

Goldberg et al. (2021) provide an earlier proof of concept for estimating visible student engagement from classroom recordings [6]. The study focuses on whether observable visual cues can be used to estimate how engaged students appear during instruction.

The approach uses machine-vision features such as gaze, head pose, and facial expressions. These signals are compared with manual ratings of visible engagement and with student self-reports. The goal is not to replace teachers, but to test whether classroom video can provide an additional indicator of engagement.

Visible student engagement in classroom instruction

Based on Goldberg et al. (2021)



Source summary: Goldberg et al., *Attentive or Not? Toward a Machine Learning Approach to Assessing Students' Visible Engagement in Classroom Instruction* (2021).

Figure 3: Constructor Tech visualization based on Goldberg et al. (2021). The figure summarizes observable indicators of visible student engagement in classroom instruction. This image was generated using artificial intelligence.

The study was evaluated on pilot recordings of three university lessons. Manual ratings of visible engagement were significantly correlated with self-reported cognitive engagement, involvement, and situational interest. They also predicted performance on a later knowledge test [6].

The machine-vision estimates were also related to manual engagement ratings. However, the study remains limited in scale and should not be treated as evidence of school deployment. It is useful mainly as an early example of how classroom video can be used to estimate engagement-related signals.

4 Adjacent TUM Research Using Gaze and Webcam Data

The projects in this section are adjacent to physical-classroom camera monitoring. They use eye tracking or webcam and microphone data to support learning, but they do not establish operational deployment of AI monitoring systems in German classrooms.

4.1 SARA and SARAKids

SARA is a TUM reading-support system that combines artificial intelligence and eye tracking. It identifies areas of written text where a learner may be experiencing difficulty and can provide tailored assistance such as additional context, sentence rephrasing, or multilingual support [11, 7].

The published SARA paper describes the system architecture and intended support workflow, but it does not report a completed classroom deployment or a learner-outcome evaluation. SARAKids applies a related approach to children learning to read. The TUM project page states that it

aims to use eye tracking to identify difficulties involving comprehension, phonetic decoding, and other reading skills, followed by personalised visual, auditory, or multimodal interventions [7]. The published page does not report a completed school trial or evaluated operational system.

These projects are relevant as examples of gaze-based, personalised learning support. They should not be presented as evidence of classroom monitoring deployment.

4.2 Video-SRS

Video-SRS concerns remote instructional-video learning rather than cameras installed in physical classrooms. The project aims to detect self-regulation problems such as mind wandering and disinterest using sensitive data from learners’ webcams and microphones. It also develops personalised federated-learning methods intended to train models on data distributed across learners’ computers [8].

The official project description states the research objectives but does not report a completed learner trial, classification-performance result, educational outcome, or operational deployment. Video-SRS should therefore be treated as an active privacy-oriented research project, not as evidence that webcam-based learning analytics has been deployed commercially or routinely in German education.

5 Conclusion

Germany should not be described as a market with broad, mature deployment of AI-based classroom monitoring in schools. The evidence supports a narrower conclusion: Germany is an active research environment for privacy-sensitive educational AI.

The strongest evidence comes from academic and university-led work on classroom video analysis, teacher visual attention, teaching-quality assessment, classroom discourse, student engagement, eye-tracking-based reading support, and self-regulated learning. These cases show experimentation, but usually under controlled research conditions rather than commercial rollout.

For K–12 education, the most credible signals are personalised learning support, privacy-sensitive learning analytics, and controlled classroom research. Public evidence of school-wide commercial deployment remains limited.

The overall pattern is cautious but meaningful. Germany is not closed to AI in education, but adoption is likely to depend on privacy-by-design, clear educational value, human oversight, institutional trust, and flexible implementation options.

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