Enacting Instructor Attention in Real Time: Comparing Haptic and Visual Alerts for Low-Disruption Instructor-Facing Classroom Support

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Abstract

This paper compares visual and haptic alerts as instructor-facing mechanisms for real-time classroom support. We treat alert delivery as an adaptation layer in teacher-facing learning analytics: the same engagement cue may impose different interaction costs depending on how it reaches the instructor. We ran a Wizard-of-Oz, within-subjects dual-task pilot with 10 proxy instructors to examine how alert modality affected acknowledgment speed, response reliability, and perceived workload during lecture delivery. Participants delivered a short prepared lecture while responding to seven engagement alerts per condition, presented either on a nearby laptop or through a smartwatch vibration. We found that participants acknowledged haptic alerts faster than visual alerts (1.84 s vs. 4.08 s) and reported lower workload in the haptic condition, whereas visual alerts yielded higher accuracy (98.6% vs. 92.9%). The findings suggest a speed-reliability trade-off in this controlled setting and indicate that adaptive classroom support may need to account for both what a system detects and which feedback channel fits instructors' attentional demands during live teaching.

Keywords

Instructor-facing classroom support, teacher-facing learning analytics, adaptive educational technology, haptic alerts, visual alerts, classroom orchestration, cognitive workload, SDG 4

1. Introduction

Student engagement is widely recognized as a central determinant of learning effectiveness, academic performance, and meaningful classroom experiences [1, 2]. This work relates to the United Nations' fourth Sustainable Development Goal (SDG 4) in a modest and indirect way: instructor-facing classroom technologies can support quality education when they help teachers notice learning needs and respond without adding avoidable interaction burden [3]. In large lectures, hybrid classrooms, and technology-mediated teaching, educators must deliver content, manage pacing, and monitor engagement at the same time. Traditional engagement monitoring methods, such as visual scanning, verbal check-ins, and post-class surveys, can be delayed, subjective, or difficult to sustain during live teaching, which limits timely instructional response.

Recent advances in educational data mining and learning analytics have enabled automated detection of engagement-related signals in classroom settings [4]. While such systems increasingly support real-time monitoring, their effectiveness depends not only on detection accuracy but also on how feedback is communicated to instructors. From a cognitive load perspective, additional interface demands may interfere with instructional performance, particularly when working memory resources are limited [5].

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Research in human–computer interaction further demonstrates that poorly timed interruptions can impair task performance and increase cognitive burden [6].

Designing effective engagement alert systems, therefore, requires careful consideration of feedback modality. Prior research on multimodal human–computer interaction indicates that visual, haptic, and ambient feedback channels present trade-offs in noticeability, interference, and cognitive demand [7, 8, 9]. Emerging work on ambient and pervasive haptic systems further highlights the potential of alternative sensory channels to support low-disruption interaction in dynamic environments [10]. However, limited empirical research has directly compared these feedback modalities within time-sensitive, dual-task instructional contexts, where instructors must manage simultaneous cognitive demands.

We grounded the modality comparison in cognitive load, interruption, and multiple-resource accounts of attention. A stationary visual alert can compete with gaze-based teaching activity, including viewing slides, scanning students, and maintaining eye contact. A wrist-based tactile cue shifts detection to a body-worn channel and may reduce visual competition, but its brief and non-symbolic form may also increase ambiguity. The comparison between laptop-based visual alerts and smartwatch haptic alerts was therefore chosen to examine a design trade-off between visual reliability and tactile immediacy, rather than to compare two arbitrary notification devices [5, 11, 12, 8].

This paper asks: How does alert modality, comparing a stationary visual display with a wearable haptic cue, affect acknowledgment speed, response reliability, and perceived workload when instructor-facing support is delivered during an ongoing lecture task? We answer this question through a controlled Wizard-of-Oz dual-task teaching scenario that compares laptop-based visual alerts with smartwatch-based haptic alerts while 10 proxy instructors continue a short prepared lecture. This paper contributes evidence about the alert-delivery layer of instructor-facing classroom support, showing how the channel used to communicate a support cue can shape interaction cost during live teaching.

2. Related Work

Prior work relevant to this design problem spans teacher-facing analytics, classroom engagement monitoring, and multimodal alert design. Research on teacher-facing analytics has increasingly shifted attention from post hoc dashboards to tools that can support instructors during ongoing classroom activity. Holstein et al [13] showed that teachers in blended and AI-supported classrooms want real-time analytics that align with immediate instructional decision-making rather than delayed reflection. Later work extended this line by exploring wearable classroom orchestration support and teacher–AI complementarity, showing that heads-up interfaces may better fit the demands of live teaching than conventional dashboards [14, 15]. At a broader level, van Leeuwen and Rummel [16] reviewed orchestration tools for teachers and found that much of the literature remains exploratory, with many systems focused on mirroring classroom information rather than delivering low-disruption, actionable support.

A second line of work has examined how engagement-related signals can be captured and presented to instructors. Aslan et al [17] demonstrated that real-time, multimodal student engagement analytics can be deployed in authentic classrooms and can improve instructor awareness of student states. Sabuncuoglu and Sezgin [18] similarly developed a multimodal classroom engagement dashboard for higher education, showing how behavioral and affective indicators can be organized for instructor interpretation. These studies make an important case for instructor-facing support, but they remain largely tied to visual interfaces. In practice, that means the instructor must still shift gaze to a display, a requirement that may compete with lecturing, classroom scanning, and other moment-to-moment teaching demands.

That evidence comes mainly from domains such as interruption management, mobile interaction, and simulated driving. For teacher-facing learning analytics, the remaining question is not whether haptics can attract attention in general, but whether a wearable tactile cue changes the cost of responding to support during lecture delivery. Direct comparisons of visual and haptic alerts for instructor-facing classroom support remain limited.

We examine alert modality as one design variable within adaptive classroom support. Future systems could personalize this variable according to alert urgency, instructor preference, teaching experience, interruption tolerance, accessibility needs, and classroom context. The present study does not model those instructor differences; it provides empirical evidence that alert channel is a plausible variable for later personalization.

3. Method

3.1. Participants and setting

Ten university participants, seven men and three women aged 20 to 25 years, served as proxy instructors in a controlled pilot. We required participants to be comfortable presenting material aloud, but prior teaching experience was not part of the eligibility criteria because the study focused on alert detection and acknowledgment during lecture-like delivery rather than expert pedagogical decision-making. All participants reported normal or corrected-to-normal vision and hearing. Participation was voluntary, informed consent was obtained before the study, and participants could withdraw at any point without penalty.

The study was conducted in a tiered university classroom arranged to preserve basic lecture cues while maintaining experimental control. Participants received a standardized slideshow several days in advance, and during the task the slides were shown on two classroom televisions. Three helpers sat in the room as student actors to provide a minimal social classroom context, although the session was not an authentic live class.

3.2. Study setup and Wizard-of-Oz alerting

We used a Wizard-of-Oz setup to compare two practical alert channels: a laptop-based visual alert and a smartwatch haptic alert. The visual channel provided a salient stationary signal that required gaze redirection, whereas the haptic channel delivered a body-worn tactile cue that could be noticed without checking a display but carried less semantic detail. To isolate alert delivery from engagement-classifier error, a facilitator near the podium triggered alerts through a smartphone control interface while observing the participant's response. Participants were told during the briefing that a classroom AI system was monitoring engagement in real time and were fully debriefed after the final session.

In the visual condition, a MacBook positioned on a nearby table within the participant's field of view displayed a blank screen during the lecture. When an alert was triggered, the screen changed to an alternating red-blue visual pattern. The participant acknowledged the alert by pressing a designated key on the laptop. In the haptic condition, the facilitator sent a vibration cue to the participant's Apple Watch. The participant acknowledged the alert by tapping the watch face. After the final session, participants were fully debriefed about the simulated nature of the system.

3.3. Procedure and measures

Each participant completed both modality conditions. The order was counterbalanced using a Balanced Latin Square, with five participants completing the visual condition first and five completing the haptic condition first. Before the experimental sessions, participants completed a short training phase with three practice alerts per modality.

During each session, participants performed a dual-task scenario. Their primary task was to deliver the prepared presentation aloud while maintaining lecture flow. Their secondary task was to notice and acknowledge engagement alerts as quickly and accurately as possible. Each condition lasted approximately five to seven minutes and included seven alerts delivered at pseudo-random intervals. This produced 14 trials per participant and 140 trials overall.

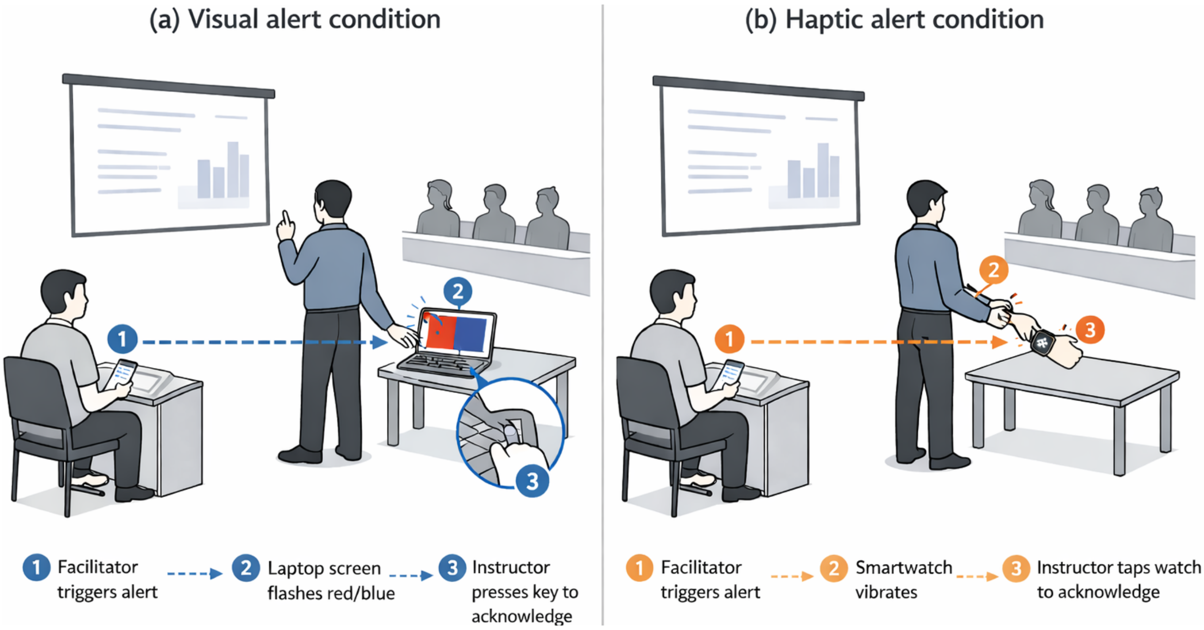

Figure 1: Experimental setup for the visual and haptic alert conditions under Wizard-of-Oz control.

Table 1
Latency and accuracy by alert modality. Latency values are participant-level mean response times.

Modality	Mean latency (s)	SD	Hit (%)	Misses	False alarms
Visual	4.08	0.66	98.6	1	0
Haptic	1.84	0.18	92.9	4	1

We operationalized low-disruption alert delivery at the interaction level by measuring the immediate cost of noticing and acknowledging a support cue while maintaining lecture delivery. Detection time captured the interval between alert onset and participant acknowledgment. Response accuracy captured hits, misses, and false alarms. Perceived workload was measured after each condition using the Raw NASA-TLX [19]. These measures calibrate interpretation around alert-response performance rather than downstream outcomes such as student learning, classroom participation, or the quality of subsequent instructional intervention. The performance item was reverse-coded during analysis so that higher values indicate better perceived performance.

We compared participant-level mean detection times between modalities using a paired-samples t-test, reflecting the within-subjects design. Cohen's d_z was calculated to estimate the paired-samples effect size. Accuracy was summarized descriptively because the error counts were sparse, particularly in the visual condition, where only one error occurred.

4. Results

The dataset comprised 140 alert trials, with 70 trials per modality. During initial screening, visual-condition response times above 10 seconds were observed for four participants. These values were retained because they appear to reflect task-related attentional delays rather than recording error.

Table 1 summarizes latency and accuracy by modality. Figure 2 shows trial-level response times for recorded acknowledgments. Visual alerts produced substantially broader dispersion, including four latency spikes above 10 s, whereas haptic responses remained tightly clustered between 1.11 s and 2.62 s. When response times were averaged within participant and compared across conditions, visual alerts yielded a mean latency of 4.08 s ($SD = 0.66$), whereas haptic alerts yielded a mean latency of 1.84 s ($SD = 0.18$). A paired-samples t-test confirmed that participant-level mean response times were higher in the visual condition, $t(9) = 9.03$, $p < .001$, with a very large effect size, $d_z = 2.85$. The mean

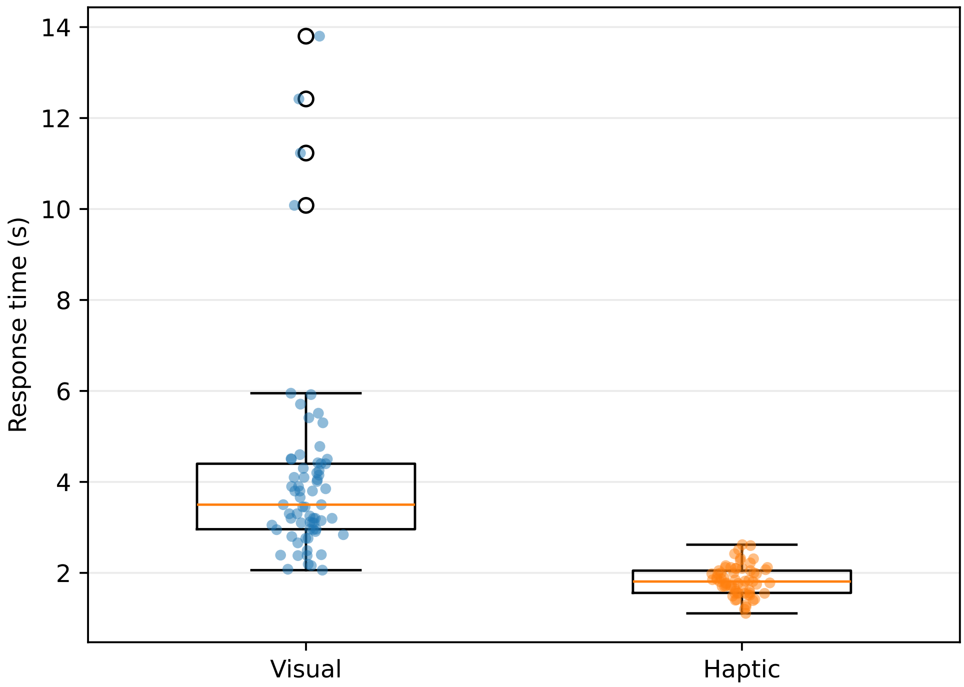

Figure 2: Response-time distribution by alert modality across valid trials.

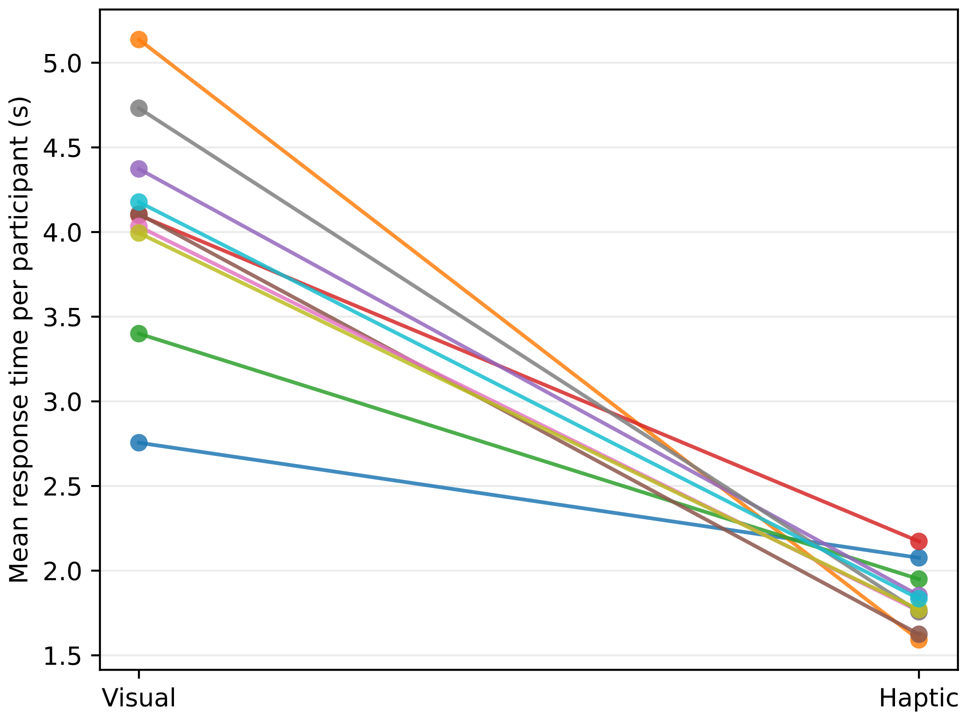

Figure 3: Participant-level paired mean response times by alert modality.

paired difference was 2.24 s, 95% CI [1.68, 2.80]. Figure 3 further shows that every participant exhibited a lower mean response time in the haptic condition.

Accuracy showed the opposite tendency. Visual alerts yielded 69 hits out of 70 trials, corresponding to a 98.6% hit rate, with one miss and no false alarms. The single visual miss occurred during the fourth alert for one participant and was annotated as occurring when the participant became distracted and

Table 2
Mean Raw NASA-TLX scores by modality. For the performance item, higher values indicate better perceived performance after reverse-coding.

Modality	Mental	Physical	Temporal	Performance	Effort	Frustration
Visual	6.1	5.0	6.0	6.6	4.9	4.7
Haptic	4.1	4.0	3.8	7.1	4.1	3.2

paused speaking. Haptic alerts yielded 65 hits out of 70 trials, corresponding to a 92.9% hit rate, with four misses and one false alarm. Two haptic misses occurred on the second alert, one on the fifth alert, and one on the sixth alert. Three haptic misses were annotated as missed vibrations, whereas one occurred while the participant was answering questions. The false alarm occurred during the seventh haptic alert sequence and was annotated as confusion involving a short feedback vibration and the notification vibration. This error profile shows that haptic cues supported faster acknowledgment but introduced more missed or ambiguous tactile events, whereas visual alerts were slower but more reliable in this controlled task.

Workload results are reported in Table 2. Haptic alerts produced lower scores on mental demand, physical demand, temporal demand, effort, and frustration. The largest difference appeared in temporal demand, which dropped from 6.0 in the visual condition to 3.8 in the haptic condition. Mental demand also decreased notably, from 6.1 to 4.1. Participants reported slightly better perceived performance in the haptic condition after reverse-coding the performance item. Overall, the workload ratings align with the response-time results: participants reported lower alert-response burden in the haptic condition during live presentation.

5. Discussion

This study examined whether the channel used to deliver an instructor-facing engagement cue changes how quickly and reliably a presenter can acknowledge that cue during ongoing lecture delivery. The results point to a speed-reliability trade-off in this pilot setting: haptic alerts supported faster acknowledgments and lower workload ratings, whereas visual alerts produced fewer errors. This finding is important for adaptive classroom support because the alert-delivery layer can shape the cost of support independently of the engagement-detection model.

5.1. Alert modality as an adaptive delivery decision

The faster responses in the haptic condition (1.84 s vs. 4.08 s) suggest that wrist-based tactile cues can reduce the need to redirect gaze from the lecture task to a fixed display. This interpretation is consistent with cognitive-load and multimodal-interaction accounts in which visual interfaces compete with other visually mediated classroom tasks, including monitoring slides, students, and room cues. The latency spikes above 10 s in the visual condition are best interpreted as moments when participants remained oriented to the presentation and did not immediately check the secondary display. They should not be treated as direct evidence of pedagogical disruption because the study did not measure student learning, student engagement, or classroom-level outcomes.

5.2. Reliability costs of single-pattern tactile cues

The haptic condition produced four misses and one false alarm, compared with one miss and no false alarms in the visual condition. The trial notes suggest two sources of reliability cost: missed tactile perception and confusion between tactile events. Three of the four haptic misses were annotated as missed vibrations, and one occurred while the participant was answering questions. The false alarm was linked to confusion involving a short feedback vibration and the notification vibration. This pattern suggests that single-pattern haptic alerts may reduce acknowledgment time but become ambiguous when instructors are speaking, answering questions, or dividing attention across classroom activity.

For instructor-facing classroom systems, misses and false alarms carry different design risks. A missed alert may delay attention to a student-engagement cue, whereas a false alarm may create an unnecessary interruption. The present study examined these risks at the alert-response level, using latency, hit rate, misses, false alarms, and workload as indicators of interaction cost. Future systems may need richer haptic encoding, visual confirmation, or adaptive channel selection to preserve the speed advantage of tactile alerts while reducing ambiguity.

5.3. Implications for personalized and hybrid classroom support

Rather than treating haptic and visual alerts as competing one-size-fits-all solutions, the findings support a hybrid and potentially personalized alert strategy. A future adaptive system could use haptic cues for time-sensitive, low-information alerts and visual confirmation for alerts requiring interpretation, prioritization, or action planning. It could also learn instructor-level preferences and constraints, such as tolerance for interruptions, teaching experience, attentional style, wearable comfort, and classroom layout. The current study does not model those instructor differences; it shows why they are worth modeling. Even in a controlled pilot, modality changed response speed, accuracy, and workload, making feedback channel a plausible personalization variable for later UMAP-oriented classroom support systems.

6. Limitations and Future Work

These findings should be read within the pilot design. The study used a small sample ($N = 10$) of proxy instructors, so the results should be read as pilot evidence on alert perception and acknowledgment during a lecture-like dual task. The classroom session was simulated with three student actors rather than conducted in an authentic course, and the study measured interaction-level indicators of disruption, including latency, errors, and workload, rather than student learning, classroom participation, or the quality of subsequent instructional intervention. Alert timing was manually controlled through a Wizard-of-Oz procedure to isolate alert delivery from engagement-classifier error. The haptic condition also used a single watch-based vibration pattern, which may have contributed to ambiguity between target alerts and other tactile sensations.

Future work should extend this pilot in four directions. First, studies with experienced instructors are needed to examine how teaching expertise, classroom routines, and presentation style shape alert response. Second, live classroom evaluations should test whether interaction-level advantages translate into better instructional timing or lower classroom disruption. Third, richer haptic vocabularies should be compared, including distinguishable vibration patterns for urgency, alert category, and confirmation. Fourth, future adaptive systems should model instructor-level and context-level factors, such as interruption tolerance, wearable comfort, attention-related accessibility needs, classroom layout, and alert urgency, to decide when haptic, visual, or hybrid delivery is most appropriate.

7. Conclusion

This study compared laptop-based visual alerts and smartwatch-based haptic alerts for instructor-facing classroom support in a controlled Wizard-of-Oz teaching task. Haptic feedback yielded faster acknowledgments and lower perceived workload, whereas visual feedback yielded higher accuracy. The results suggest that alert modality creates a practical speed-reliability trade-off in this pilot setting. The study does not establish direct effects on learning or teaching quality; instead, it identifies alert delivery as a design variable for adaptive classroom support. Future work should test whether these patterns hold with larger samples of experienced instructors, richer haptic encodings, and live classroom contexts.

Declaration on Generative AI

During the preparation of this manuscript, GPT-5 was used for language editing and formatting support. The authors retained full control over the study design, analysis, interpretation, and final wording of the paper, and they take full responsibility for its content.

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