Computers & Education 206 (2023) 104912

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Body in motion, attention in focus: A virtual reality study on teachers' movement patterns and noticing

Yizhen Huang [a,b,*], Eric Richter [a], Thilo Kleickmann [b], Katharina Scheiter [a], Dirk Richter [a]

[a] *Department of Education, University of Potsdam, Karl-Liebknecht-Str. 24-25, 14476, Potsdam, Germany*
[b] *Department of Research on Teaching and Teacher Education, Kiel University, Olshausenstraße 75, 24098, Kiel, Germany*

A R T I C L E I N F O

Keywords:
Augmented and virtual reality
Data science applications in education
Improving classroom teaching
Simulations
Teacher professional development

A B S T R A C T

When people navigate a space to perform tasks, their body and eye movements are closely linked. Within the classroom context, characteristics of teachers' body movements may be related to the noticing of relevant classroom events, in particular, visual attention to student disruptions. In the current study, we investigated this relationship in an immersive virtual reality (IVR) classroom that offered a standardized environment for tracking teachers' body and eye movements. Based on time series data collected during a short teaching task with 21 preservice teachers, we conducted K-means clustering with body movement features. We identified three distinctive patterns, which we labeled as immobile, anchored, and dynamic (body) movement patterns. Teachers with dynamic movement patterns venture away from the teacher's desk to far corners of the room; they don't dwell in one location for long but rather move continuously to various parts of the classroom, creating a dispersed movement. Dynamic movement patterns were associated with the best *visual attention performance,* defined as the number, speed, and duration of fixations on a classroom disruption. Our findings demonstrate the existence of unique and differentiable movement patterns among preservice teachers that have implications for teacher noticing, teacher–student interaction, and instructional quality.

1. Introduction

Preservice teachers often face significant challenges distributing and directing their visual attention in the classroom and noticing critical events. They have been found, for instance, to overlook incidents such as student disruptions and opportunities such as "teachable moments" (Gegenfurtner et al., 2019; König et al., 2022; Stockero et al., 2017). The challenge of noticing is important to address since instructional decisions rely first and foremost on accurate and prompt visual attention to classroom events. The ability to visually attend to specific objects in a selective and timely manner is referred to as *visual attention performance* in the vision research (Dye & Bavelier, 2010; Laasonen et al., 2012). Theoretical research in education has described teachers' visual attention performance as a key component of their *professional vision*: "the ability to notice and interpret significant features" in a classroom (Sherin & van Es, 2009, p. 20). Professional vision enables teachers to identify what is important or noteworthy about a classroom situation (Seidel & Stürmer, 2014).

* Corresponding author. Department of Education, University of Potsdam, Karl-Liebknecht-Str. 24-25, 14476, Potsdam, Germany.
E-mail addresses: yihuang@uni-potsdam.de (Y. Huang), eric.richter@uni-potsdam.de (E. Richter), kleickmann@paedagogik.uni-kiel.de (T. Kleickmann), katharina.scheiter@uni-potsdam.de (K. Scheiter), dirk.richter@uni-potsdam.de (D. Richter).

https://doi.org/10.1016/j.compedu.2023.104912
Received 10 March 2023; Received in revised form 29 June 2023; Accepted 31 August 2023
Available online 1 September 2023

As a first step toward improving teachers' visual attention performance, recent research has sought to identify the associated factors (for a review, see König et al., 2022). Some studies have focused on internal factors, such as teaching experience (Gold & Holodynski, 2017), teaching scripts (Wolff et al., 2020), and mental organization strategies (Geeraerts et al., 2018), while others have examined external factors, such as the teaching task (Stahnke & Blömeke, 2021) and the degree of classroom disruptions (Huang et al., 2021).

The question of how teachers move around the classroom environment has long been overlooked in efforts to uncover factors related to teachers' visual attention performance, despite the widely acknowledged interplay between human vision and motion (Goodale, 1998; Hayhoe, 2017). Moving around and performing tasks in the real world requires a coordinated system involving both the eyes and the body, known as visuo-motor control (Foulsham et al., 2011; Land & Tatler, 2009). Recent research on mobility behavior suggests that individuals' body movement patterns exhibit distinctive features that are stable over time. In this context, features such as the distance traveled, the amount of time spent in one place, and the degree to which movement is evenly distributed have been shown to have a high degree of spatial and temporal regularity (González et al., 2008). Various studies have shown that the ways people look at their environment are entangled with how they move within it (e.g., Carrasco, 2018; Patla & Vickers, 2003).

In the classroom context, teachers often move around for different tasks that require their attention: They stand at the front of the room to use the projector, walk around to students' desks to check their work, or address misbehavior, and move back to the front to address the class as a whole. The ways teachers move, that is, their (body) movement patterns, may therefore offer rich insights into the ways they allocate their visual attention. Mobile eye tracking studies have revealed that preservice teachers often visually fixate on objects that are closer to them spatially (Huang et al., 2023; McIntyre & Foulsham, 2018).

To investigate the potential associations between preservice teachers' movement patterns and visual attention performance, their movement and eye movement metrics must be measured simultaneously as they are teaching, while at the same time controlling for environmental influences. This has not been possible so far due to a) a lack of concurrent tracking of motion and eye movements during teaching, and b) the wide variety of classroom environments in terms of physical settings, student characteristics, and classroom events. Immersive virtual reality (IVR) technology has proven instrumental in overcoming these practical challenges. IVR allows users to see, hear, and move freely in a realistic 3D environment (Huang et al., 2023; Bailey & Bailenson, 2017; Radianti et al., 2020). Recently developed IVR hardware is also capable of tracking users' body and eye movements while they are interacting with the VR environment (Clay et al., 2019; Hasenbein et al., 2022).

In the present study, we used IVR technology to present a VR classroom in which both the setting and events are standardized (see 2.2 Material and Equipment: VR Classroom for details). We classified preservice teachers' movement patterns based on time series movement tracking data collected while they were teaching in the IVR classroom. We then linked the identified movement patterns with teachers' actual visual attention performance, defined as the number of times they focused their visual attention on each ongoing student disruption (see off-task events in Table 1), the speed and duration of fixations on such disruption.

1.1. *Teacher's Visual Attention Performance*

Classrooms are dynamic and complex environments that impose heavy demands on teachers' attention resources (Clarridge & Berliner, 1991; Doyle, 1977; Kounin, 1970). At any given time, teachers have to perform multiple tasks simultaneously, such as giving a lecture, distributing worksheets, and using instructional technologies, all while keeping an eye on the entire class (Doyle, 2006).

Teachers' ability to pay attention to incidents such as student disruptions[1] in a situation of high environmental complexity is key to making sound instructional decisions in the face of these demands. This ability has been described in various research traditions as situation awareness (Endsley, 1988; Miller, 2010), situation-specific perception (Blömeke et al., 2015), vigilance (Parasuraman, 1986), withitness (Kounin, 1970), noticing (Jacobs et al., 2010), and the most comprehensive construct of all, professional vision (Sherin et al., 2010; Sherin & van Es, 2009).

Within the latter body of research, p*rofessional* vision is considered a core aspect of teachers' professional expertise, but there is a lack of agreement on its constitutive elements (for reviews, see König et al., 2022; Stahnke et al., 2016). The classic framework by van Es and Sherin (2002) describes professional vision as a construct with three aspects: paying selective attention to significant classroom events, making connections between events and pedagogical principles, and knowledge-based reasoning about the events. Jacobs et al. (2010) extended the confines of this framework by adding the planning and execution of actions by teachers after they have engaged in selective attention and knowledge-based interpretation. Similarly, Blömeke et al. (2015) additionally included the aspect of decision-making as part of professional vision in their perceive-interpret-decide (PID) model. Star and Strickland (2008), in contrast, narrowed the conceptualization of teachers' professional vision to selective attention.

Despite the differences in these frameworks, they all overlap in the initial step of teachers' professional vision: the perception of the classroom event or feature. Naturally, the perception of critical events in the classroom is a prerequisite for all further interpretation or action. Improving teachers' perceptual capacity to select and focus on important classroom events in a timely manner—that is, teachers' visual attention performance—is therefore vital for improving instructional quality and educational outcomes (Blömeke et al., 2022; Keller et al., 2022).

Distributing visual attention in the complex classroom environment is challenging for most teachers, but especially for preservice teachers. Compared to more experienced teachers, preservice teachers have been found to process information more slowly and to distribute visual attention less evenly when watching classroom videos (Keller et al., 2022; Wolff et al., 2016). This finding has been

[1] Student disruptions and misbehaviors were used interchangeably in the present study to describe student-initiated classroom events that distract teachers from their primary program of action.

Table 1
Behavior Script of Student Agents

Event ID	Event start time (seconds)	Agent location	Behavior	Category
1	340	02L	Play with a pen	off-task
2	355	02L	Write on the notebook	on-task
3	340	10L	Stare outside the window	off-task
4	355	10L	Idle	–
5	350	11L&R	Chat with the neighbor	off-task
6	365	11R	Idle	–
7	365	11L	Idle	–
8	360	14L	Throw paper balls	off-task
9	375	14L	Idle	–
10	360	15L	Play with a pen	off-task
11	375	15L	Idle	–
12	370	03L&R	Chat with the neighbor	off-task
13	385	03L	Idle	–
14	485	03R	Write on the notebook	on-task
15	370	14R	Stare outside the window	off-task
16	385	14R	Idle	–
17	380	06L	Throw paper balls	off-task
18	395	06L	Idle	–
19	390	07L&R	Hit the neighbor	off-task
20	405	07R	Idle	–
21	405	07L	Idle	–
22	395	11L	Stare outside the window	off-task
23	395	11L	Idle	–
24	410	10R	Drink soda	off-task
25	425	10R	Idle	–
26	420	01L&R	Hit the neighbor	off-task
27	435	01R	Idle	–
28	435	01L	Idle	–
29	435	12L&R	Chat with the neighbor	off-task
30	450	12L	Idle	–
31	450	12R	Write on the notebook	on-task
32	450	10R	Raise arm	on-task
33	454	10R	Ask a question	on-task
34	464	10R	Idle	–
35	455	12R	Throw paper balls	off-task
36	465	12R	Idle	–
37	455	12L	Eat an apple	off-task
38	470	12L	Idle	–
39	470	11L&R	Chat with the neighbor	off-task
40	485	11R	Idle	–
41	485	11L	Idle	–
42	480	06L&R	Hit the neighbor	–
43	495	06L	Idle	–
44	495	06R	Idle	–
45	480	02L	Play with a pen	off-task
46	495	02L	Idle	–
47	495	13L&R	Hit the neighbor	off-task
48	510	13L	Idle	–
49	510	13R	Idle	–
50	510	14L&R	Hit the neighbor	off-task
51	525	14R	Idle	–
52	525	14L	Idle	–
53	530	03L&R	Chat with the neighbor	off-task
54	545	03L	Idle	–
55	545	03R	Idle	–
56	550	04L	Throw paper balls	off-task
57	565	04L	Idle	–
58	550	10R	Raise arm	on-task
59	552	10R	Ask a question	on-task
60	562	10R	Idle	–
61	565	01L&R	Chat with the neighbor	off-task
62	580	01L	Idle	–
63	580	01R	Idle	–
64	570	07R	Stare outside the window	off-task
65	585	07R	Idle	–
66	570	06L	Throw paper balls	off-task
67	585	06L	Idle	–
68	570	02L	Eat an apple	off-task

(*continued on next page*)

Table 1 (*continued*)

Event ID	Event start time (seconds)	Agent location	Behavior	Category
69	585	02L	Idle	–
70	580	13R	Play with a pen	off-task
71	595	13R	Idle	–

Note. Idle is the default behavior: agents would sit naturally in various neutral poses and move their eyes or body to follow the users around. After performing either on- or off-task behaviors (automatic termination after 15 s), agents would return to the idle state. Other than the off-task behaviors involving a neighbor (two agents misbehave together), different off-task behaviors did not overlap in time. There were 30 off-task events with 42 individual student disruptions.

replicated with eye tracking studies, both in video viewing (Kosko et al., 2022; Seidel et al., 2011), staged scenarios (Stürmer et al., 2017), and real-life instructional situations (Huang et al., 2023; McIntyre & Foulsham, 2018). After comparing the eye movements of 25 pairs of teacher trainees and their trainers, Huang and colleagues (2023) found that preservice teachers were slower at switching visual focus, looked at irrelevant objects more often, and paid visual attention to a significantly smaller area.

Considering the significance of visual attention performance and the challenges that preservice teachers face in developing it, it is critical to understand the associated factors. On the one hand, preservice teachers have been shown to have less efficient information organization and cognitive processing ability, which is reflected in how they distribute visual attention (Charness et al., 2001; Gegenfurtner et al., 2022). According to perceptual encoding theory (Reingold et al., 2001), their smaller visual fields may be explained by a less developed ability to encode information in large and coherent chunks. On the other hand, features of the instructional environment could also affect preservice teachers' visual attention performance. For instance, the instructional format (partner work vs. whole-group work) can affect novice teachers' visual attention allocation to students (Stahnke & Blömeke, 2021), and the amount and degree of student disruptions can affect their likelihood of accurately identifying and paying attention to the disruption (Huang et al., 2021).

Another factor that is likely related to visual attention performance but that has rarely been investigated is the individualistic characteristics of teacher's movement within the classroom, i.e., the movement pattern. When people navigate an environment to perform tasks, such as going from desk to desk to check students' work, their bodily movements (motor system) and eye movements (visual system) are tightly intertwined to meet the demands of the task at hand (Foulsham et al., 2011; Hayhoe, 2017). This strong relationship between motion and vision indicates a potential association between movement patterns and visual attention performance among preservice teachers.

1.2. Looking and Moving: Human Movement nd Visual Attention

The term human motion[2] refers to all human-generated movements at both the micro and macro level (Aggarwal & Cai, 1999). Micro-level locomotion is characterized by small muscle movements such as twitching and gesturing with the hands, whereas macro-level motion focuses on the movement trajectory of the entire body rather than its parts in three-dimensional (3D) spaces. Teachers' movements within the classroom would therefore be considered macro-motion.[3]

Patterns of human movement over a spatial range are considered to be stable over time: for instance, the distance a person travels, the amount of time they stay in one place, and the degree to which their movement is evenly distributed (González et al., 2008; McInerney et al., 2013). Such idiosyncratic and classifiable characteristics of human movement are called *movement patterns* (Aggarwal & Cai, 1999; Dodge et al., 2008).

The advancement of concurrent motion and eye movement tracking technology (e.g., Han, 2021; Jogeshwar & Pelz, 2021) has prompted various perspectives to investigate the connections between movement patterns and visual attention performance. First, natural behaviors can be considered as a series of "sensory-motor decisions" that require both visual and motor systems (Hayhoe, 2017, p. 389). The primary function of vision in this decision-making chain is to gather relevant information to choose a course of action, such as how or where to move the body (Maloney & Zhang, 2010). Eye movement toward a relevant location, for instance, is often initiated "just-in-time" before the actual body movement (Ballard et al., 1995). Mobile eye tracking studies have shown that participants focus their gaze (fixate) on a target location approximately a second before placing their foot in that location (Patla & Vickers, 2003). Similarly, athletes often look at the spot where they expect a ball in flight to be tens of milliseconds in advance of its arrival in that spot (Hayhoe & Ballard, 2005; McKinney et al., 2008).

Second, not only does the visual system aid the motor system in goal-oriented actions; it also requires the support of the motor system to perform its functions. Due to the anatomical structure of human eyes, only in the small foveal area at the center of retina can we see clearly at high resolution: Visual acuity drops by a factor of 10 at 20 degrees of eccentricity from the fovea's center (Land & Tatler, 2009). The restriction of foveal vision propels the movement of the entire body to position the most relevant information at the center of the fovea. Moving closer to the object of interest is one such movement (Hamm et al., 2019), since visual acuity increases dramatically as the distance between the eyes and the object reduces within a range of around 6 m (Tidbury & O'Connor, 2015).

[2] Also referred to as human dynamic (Yuan, 2018), (loco)motor behavior (Adolph & Franchak, 2017), mobility behavior (Müller et al., 2020), and spatial behavior (Ai et al., 2019).

[3] Motion and movement are used interchangeably in this study to represent macro-level human motion.

Visual acuity is essential for judging whether someone is looking at you. This is especially relevant for teachers, who often look at students' faces to assess whether they are paying attention. Accuracy in mutual gaze perception is highest within a distance of 2 m (Gamer & Hecht, 2007). Eye tracking studies have also reported "eccentricity effects" in the relationship between distance and visual attention performance (Koivisto et al., 2004): Changes occurring close to where the eye is fixated are detected more quickly and accurately than changes occurring further away (Hollingworth et al., 2001).

A third perspective on the relationship between body movement and visual attention performance relates to the existence of *peripersonal space*, the space immediately surrounding the human body in which physiological and behavioral responses to stimuli are stronger (Rizzolatti et al., 1997). Neurophysiological responses to objects within this peripersonal space differ from responses to objects in extrapersonal space (Bufacchi & Iannetti, 2018; Holmes & Spence, 2004) and produce significantly more accurate and faster visuomotor responses. For instance, participants perform better at visual attention tasks including visual search when their hands are near rather than far from the stimulus (Abrams et al., 2008; Brozzoli et al., 2014). Such positive visual attention bias toward objects within the peripersonal space is also accompanied by faster tactile stimulus detection (Làdavas et al., 1998) and action execution (Costantini et al., 2010).

As teachers move around the classroom, their visual acuity, the boundaries of their peripersonal space, and the students within this space also change. Their visual attention performances, i.e., how accurate and timely they could visually focus on important classroom events, is therefore likely to be related to how they move in the classroom.

Eye tracking studies conducted in real classrooms have demonstrated that both expert and novice teachers tend to look more at locations in close spatial proximity to where they are standing (Huang et al., 2023) and that students sitting in the *T-zone* (first row and middle section) closer to the teacher receive more visual attention (Smidekova et al., 2020). This increased visual attention may in turn lead to better learning outcomes (Blume et al., 2019). Early studies on teachers' movement behavior also indicated that effective teachers spent more time moving around and paying attention to students' activities (Behets, 1997).

Despite the evidence of idiosyncratic patterns in body movement, research to date has overlooked the unique patterns of teachers' body movements and the potential associations between these patterns and teachers' visual attention performance. The challenge in identifying such patterns lies above all in the great variability of the natural classroom environment and events that affect human body and eye movement. Complete standardization of classroom environments and events for the purpose of investigation is hardly achievable in real-life classrooms. An immersive virtual reality classroom in which teachers can move and look around freely and experience realistic but standardized situations therefore offers a useful setting for investigating the relationships between movement patterns and visual attention performance.

1.3. The Immersive Virtual Reality Classroo

Virtual reality (VR) is a collection of digital technologies that enable creation of realistic experiences in virtual environments (McGarr, 2021). Among the various VR systems, (fully) immersive VR (IVR) systems provide the highest level of sensory fidelity by offering nearly all of the visual and auditory information available in a physical environment (Bailey & Bailenson, 2017; Slater, 2018). This is often accomplished with 360° visuals through a head-mounted display (HMD), directional auditory input via headphones, and limb proprioception via controllers and tracking sensors (Radianti et al., 2020).

Immersive VR classrooms allow users to act like teachers and students in a comparable way to real life. They can walk around with their own limbs; what they see and hear changes in line with their head and body movements; and most importantly, they feel present in this environment. Because of the high level of realism and controllability, IVR classrooms have gained great traction in recent research: Seufert et al. (2022) developed an IVR classroom in which preservice teachers practiced and developed classroom management competencies; Chen (2022) used a similar IVR classroom to improve the speed and effectiveness of preservice teachers' classroom management behavior; Blume (2019) investigated whether positioning students closer to a virtual teacher in the IVR classroom would improve their learning outcomes; and Richter and colleagues (2022) used IVR classroom videos to facilitate self-reflection efficacy among preservice teachers (for a review, see Huang et al., 2023).

Besides recreating an authentic and configurable classroom environment, IVR also enables continuous, multi-modal data collection that captures the rich nature of classroom behaviors. Teaching in a classroom, even for a very short period, is characterized by a variety of concurring task demands such as spatial navigation, speech generation, human interaction, and technology operation. Teaching is a complex, highly dynamic process that should be investigated utilizing a wealth of data sources. To date, however, research has mainly used only subjective reports and observation. IVR can fill this gap by collecting diverse types of time-series data simultaneously, including data on spatial location, eye movement, speech, and teachers' behavior. On the topic of the present study, human-subject research has used motion and eye tracking in IVR, for instance, in scene perception (Anderson et al., 2021), spatial navigation (Armougum et al., 2019), and instructional design (Baceviciute et al., 2022). Recently, Hasenbein et al. (2022) used eye tracking in an IVR classroom to investigate students' visual attention and learning experiences in different social settings (also see Gao et al., 2021).

To summarize, observing preservice teachers in an IVR classroom allows us to a) track their movement and eye movement unobtrusively and accurately, and b) maintain a balance between realism and standardization of the classroom environment (physical setting, student characteristics, classroom events, etc.). This enables us to investigate relationships between preservice teachers' movement patterns and visual attention performance.

1.4. Present Study

Given the close interconnections between the visual and motor system in natural behavior, patterns of teachers' body movement trajectories over time may be closely related to their visual attention performance. To investigate these relationships, however, we first need to control for known factors in visual attention performance: the level of teachers' expertise, and features of the instructional scenario (instructional format, classroom setting and events, etc.). The present study used a standardized IVR classroom capable of motion and eye tracking to investigate preservice teachers' visual attention performance while carrying out a teaching task. Specifically, our research questions were as follows:

RQ1. Are there distinctive patterns of preservice teachers' movement when teaching in an IVR classroom?

RQ2. If so, do teachers differ in visual attention performance—number, speed, and duration of fixations on each student disruption—in relation to these movement patterns?

The design of this study and the analysis were preregistered at https://osf.io/23w68/.

2. Methods

2.1. Participants

The current study focuses on preservice teachers who are enrolled in university-based teacher education programs and have minimal prior teaching experience. Twenty-one preservice teachers were recruited from a weekly seminar on classroom management held at a public German university ($M = 22.2$ years, 55% female, 96.9% bachelor program). The demographic characteristics are representative of this population (e.g., Huang et al., 2022, 2023; Seufert et al., 2022). This sample was chosen given that it was easy to access and representative of the population of interest. All participants were studying to become teachers and had no prior experience with the IVR classroom. The participation in IVR session was an integral part of this seminar but not demanded.

2.2. Material and Equipment: IVR classroom

Our IVR classroom had 30 virtual students (agents[4]) arranged in five rows and three columns. The virtual students possessed diverse physical features (see Fig. 1, top right), and their behaviors were programmed (see Table 1). Participants of similar backgrounds in earlier studies reported this IVR classroom to be authentic and believable.

Participants were immersed in the IVR classroom through the HTC Vive Pro Eye system with Tobii XR (Tobii, 2021). The Pro Eye headset has a resolution of 1440×1600 pixels per eye with a 110° field of view. It is capable of recording eye movements at a sampling rate of 120Hz with 0.5°–1.1° accuracy and has been widely used in eye tracking studies (e.g., Hasenbein et al., 2022; Shadiev & Li, 2023; Stein et al., 2021). Besides the high visual and audio fidelity, this system also provides room-scale tracking, allowing participants to walk around in the physical reality while receiving corresponding sensory signal in the IVR classroom. The participants have the option to "teleport" to specific locations within the classroom in cases where it may be difficult to access by walking. The participant's location, which is represented by (X, Y) coordinates sampled at every second, is tracked by this system.

2.3. Procedure: Teaching Task

Participants first listened to a 5-min audio instruction to familiarize themselves with the IVR classroom. They then gave a 4-min lecture in the IVR classroom about COVID-19 vaccinations, during which they had to respond to typical classroom disruptions. The lecture topic was predetermined, and participants had a week to prepare the lesson with the presentation slides and lesson plan that would be used in the IVR classroom. During the participant's lecture, virtual students engaged in both on- and off-task behaviors (see Table 1) that are common in secondary classrooms (Borko, 2016; Wolff et al., 2016). Students' behaviors were initiated independently of the teachers' actions.

2.4. Measures

Participants' eye and body movements were collected continuously during the IVR teaching task. Specifically, eye movement was recorded as a sequence of fixations with fixation onset time, fixation duration, and fixation location. Based on piloting and previous studies (e.g., Anderson et al., 2021; Gao et al., 2021), the fixation was defined with the thresholds of a minimum duration of 100 ms and a maximum dispersion of 3°. Fixation locations were extrapolated by computing the intersection of gaze direction in the virtual space, taking head locations and orientations of participants into account (see details in Appendix B).

Movement was recorded as time series data sampled at every second with the participant's location in the two-dimensional projection of the IVR classroom. Eye and body movements could be regarded as point patterns—datasets with observed spatial locations of things or events (Baddeley et al., 2016). The locations were therefore represented as X–Y coordinates within a two-dimensional coordination system, i.e., the IVR classroom room map (see Fig. 1 left for the room map).

First, the raw movement data were used to calculate eight summary statistics that are commonly used in spatial point pattern analysis to capture the features of physical movement, such as the degree of dispersion and regularity (González et al., 2016; Illian

[4] Avatars and agents are two types of "virtual humans" in VR. An avatar is a computer-generated character whose actions are governed by a real human being, while an agent's actions are programmed (Kyrlitsias & Michael-Grigoriou, 2018).

Fig. 1. View of the IVR Classroom. *Note.* Left: room map; top right: front view from the teacher's desk; bottom right: view from the second row. Views on the right were displayed from the participant's first-person perspective.

et al., 2007). The most prominent of these statistics are the Clark-Evans index (*CE*) (Clark & Evans, 1954) and the pair correlation function $g(r)$. *CE* is a classic scale-invariant measure of point aggregation based on nearest-neighbor distance. It is the average distance between a point and its nearest neighbor divided by the average distance between points generated by a Poisson process of the same intensity (Illian et al., 2007). Therefore, $CE = 1$ if the point distribution is completely random (identical with the Poisson process); $CE > 1$ if the point pattern shows a propensity towards regularity (even distribution); $CE < 1$ indicates aggregation of points associated with certain patterns; and a smaller *CE* means higher aggregation in this range. The pair correlation function $g(r)$ is another important second-order functional summary statistic that represents the ratio between the number of pairs of points that are r units apart and the corresponding probability if the point process is random (Baddeley et al., 2016). $g(r)$ reaches one when the observed point process is completely random. The boundary r value when $g(r) = 1$ can thus be interpreted as the size of a point cluster. We also included six other statistics that plainly capture the characteristics of teachers' movements such as the mean and standard deviation of the distances between consecutive participant locations and the duration of each stay (see Table 2 for all summary statistics and brief explanations).

Second, since visual attention performance in the classroom could be defined as the ability to select and focus on important classroom events in a timely manner (Dye & Bavelier, 2010), we operationalized participants' visual attention performance in the current teaching task as the number of fixations on each ongoing student disruption (see off-task events in Table 1), the time to first fixate (or fixation speed), and the total duration of fixations on such disruption. Fixation speed and duration were measured in seconds. As shown in Table 1, there were 30 off-task events with 42 individual student disruptions during the teaching task.

In addition to measurements of body movement and gaze behavior, we also assessed sociodemographic characteristics of the participants. Participants reported their age, A-level grade (Abitur), semester, classroom management experience, VR experience, and preparedness for the IVR teaching task in a questionnaire prior to the IVR teaching task.

In the questionnaire, we also measured two covariates that could be related to participants' behaviors and experiences in teaching an IVR classroom. First, classroom management self-efficacy is the belief about one's ability to "organize and execute the courses of actions" (Bandura, 1997, p. 3) in classroom management (Aloe et al., 2014). A positive relationship between IVR experience and self-efficacy has been reported in previous studies (e.g., Huang et al., 2023; Gundel et al., 2019; Makransky et al., 2020). This construct was measured with five items adapted from the Teacher's Sense of Efficacy scale (Pfitzner-Eden, 2016; Pfitzner-Eden et al., 2014) (sample item: "I can get students to follow rules in class."; four-point Likert scale from 1 = "does not apply at all" to 4 = "fully applies"; $\alpha = 0.79$). Second, cognitive load is a measure of the amount of mental effort required to complete a cognitive task (Plass et al., 2010; Salomon, 1984) and have frequently been identified to be associated to IVR experience (e.g., Albus et al., 2021; Andersen & Makransky, 2021; Huang et al., 2023) as well as eye movement measures (e.g., Zargari Marandi et al., 2018; Zu et al., 2020). Perceived

Table 2
Descriptions of Point Pattern Summary Statistics.

	Summary statistic (short code)	Description
1	Clark-Evans index (*CE*)	Clark-Evans index of movement point pattern is a scale-invariant measure of point aggregation. Interpreted roughly as standardized nearest neighbor distance, thus smaller *CE* between 0 and 1 means higher aggregation.
2	r of $g(r) = 1$ (r)	r value of movement point pattern when pair correlation function $g(r) = 1$ represents size of the point cluster.
3	Mean fixation-location distance (dist_em_m)	Mean distance between fixation location and participant location.
4	SD fixation-location distance (dist_em_sd)	Standard deviation of the distances between fixation location and participant location.
5	Mean location distance (dist_loc_m)	Mean distance between consecutive participant locations.
6	SD location distance (dist_loc_sd)	Standard deviation of the distances between consecutive participant locations.
7	Mean dwell duration (dwe_dur_m)	Mean duration of stay in one location.
8	SD dwell duration (dwe_dur_sd)	Standard deviation of the durations of stay in one location.

cognitive load was measured by the widely used mental effort rating scale by Paas (1992). Participants rated their "invested mental effort during the task" on a 9-point Likert scale (1 = very low mental effort to 9 = very high mental effort) (see Table A1 in Appendix A for all items).

2.5. Statistical Aalyses[5]

RQ1 inquired whether there are distinctive patterns of preservice teachers' movement. This research question can be rephrased as a question of whether participants can be classified into subgroups according to their movement features during IVR teaching. This is a classic unsupervised learning problem: "finding groups in data without the help of a response variable" (Tibshirani et al., 2001, p. 411). Clustering is a collection of exploratory data analysis methods developed to solve this kind of problem. It is widely used to determine the naturally distinct groupings of individual observations based on their feature vector. Clustering methods have been used, for instance, to identify high-risk populations with gene expressions (Kerr et al., 2008), to partition customer interests with search queries (Mecca et al., 2007), and to group unique physical behavior patterns (Leech et al., 2014). K-means clustering is the most widely accepted clustering algorithm when all the features are quantitative variables (Hastie et al., 2001), which was the case in the present study. We therefore employed K-means clustering with preservice teachers' spatial-temporal features of movement sequences. All analyses were conducted in R version 4.1.2 (R Core Team, 2021) with spatstat (Baddeley et al., 2016), FactoMineR (Lê et al., 2008), factoextra (Kassambara & Mundt, 2020), fpc (Hennig, 2020), and lme4 (Bates et al., 2015).

The starting point of K-means clustering is to select and produce a feature vector that captures the characteristics of interest for a certain observation (see Fig. 2 for an overview of steps). As described in the Measures section, eight commonly used summary statistics that capture the characteristics of physical movement as a point pattern process were used in the feature vector (see Table 2). All summary statistics were then scaled to have a mean of zero and standard deviation of one (James et al., 2013).

With these eight summary statistics, we needed to further reduce the dimensionality of the feature space using principal component analysis (PCA). Dimension reduction with PCA is essential to optimize the process of searching for solutions to the K-means algorithm when the original feature space is large (James et al., 2013; Xu et al., 2015). The number of PCA components to be included could be determined through a combination of the scree plot and rule of thumb approach (Hastie et al., 2001) (see Appendix B for more details).

In the next step, we took a data-driven approach to initiate the K-means clustering with two methods: Both the scree plot of the total within sum of square (WSS) and the gap statistic were considered when estimating the optimal number of clusters to initiate K-means clustering. The number of clusters was determined by a) locating the turning point at which adding another cluster does not substantially reduce the WSS (Hastie et al., 2001), and b) maximizing the differences, that is, the gap between the observed and expected values of log WSS (Tibshirani et al., 2001) (see Appendix B for details).

As the last step to answer RQ1, the quality of the partitioning generated by K-means clustering was validated with commonly used internal validation measures. Internal measures assess the quality of the clustering result without referring to external information that is suitable for an unsupervised learning task such as ours (Liu et al., 2010). First, the silhouette index (S) was used to quantify the pairwise difference of intra- and inter-cluster distances. Observations with a large S that is closer to 1 are well clustered. Second, the S_Dbw index (*S_Dbw*) measures the inter-cluster separation (Halkidi & Vazirgiannis, 2001). A smaller *S_Dbw* therefore indicates a better clustering result.

After distinctive subgroups based on preservice teachers' movement features were identified and validated, we examined whether the subgroups differed in visual attention performance (RQ2). We used linear mixed (-effects) modeling (LMM) to evaluate the effect of cluster assignment as well as covariates on participants' visual attention performance.

[5] Data and primary analyses are available on the Open Science Framework: https://osf.io/23w68/.

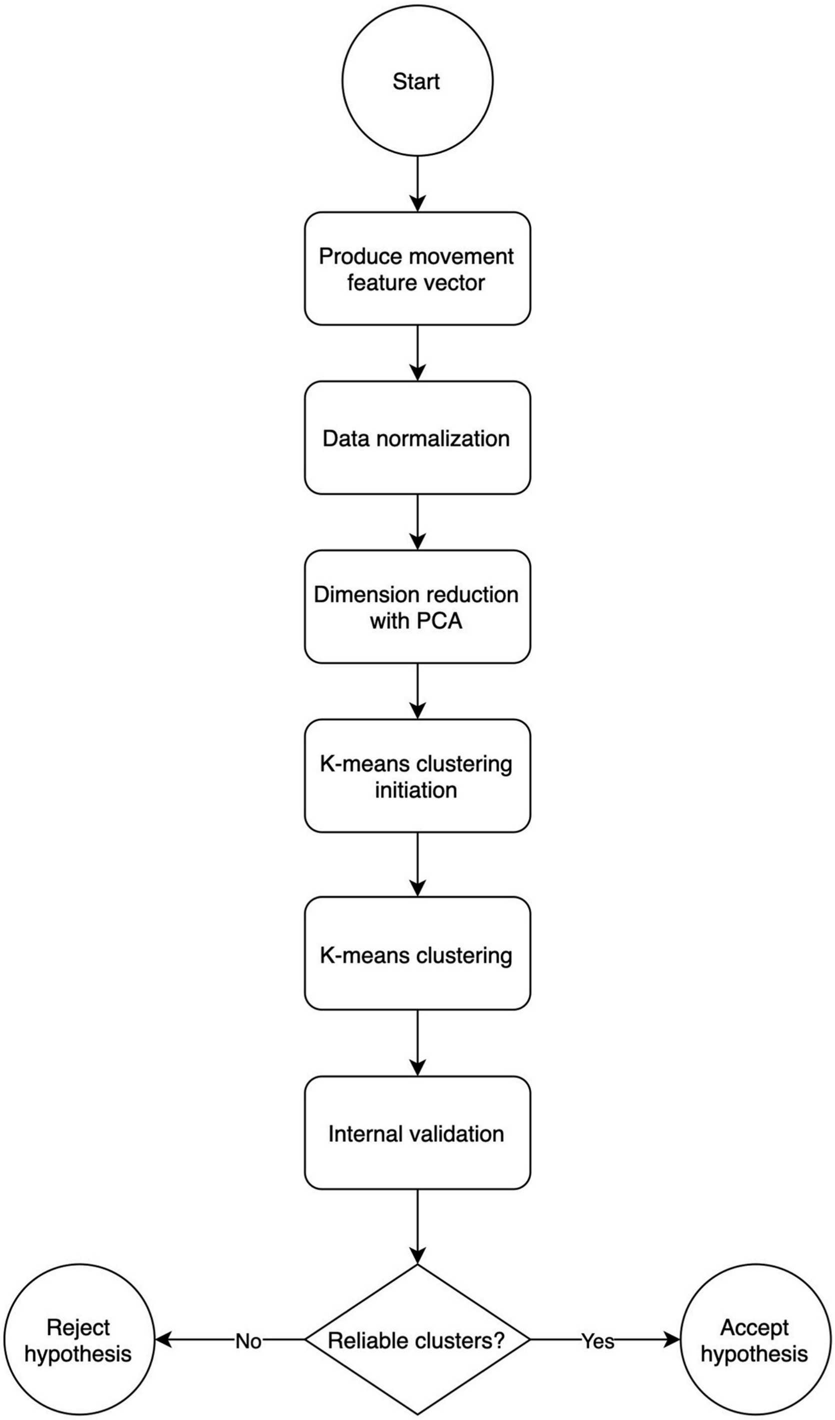

Fig. 2. Flowchart of K-Means Clustering Steps. *Note.* For a similar representation, see Ivanová et al. (2022, p. 4).

3. Results

3.1. RQ1: Identify Movement Patterns

According to the steps outlined in Fig. 2, we first produced the movement feature vector based on eight summary statistics that described the teachers' movements as point pattern processes (see Table 3 for descriptive statistics). We then reduced the dimensionality with PCA (see Table A2 in Appendix A). Based on the scree plot and rule of thumb, the first two principal component score

Table 3
Descriptive of Movement Summary Statistics.

	Cluster	*CE*		*r*	dist_em_m		dist_em_sd	dist_loc_m		dist_loc_sd		dwe_dur_m		dwe_dur_sd	
Mean	1	0.042		1.429	8.369		4.344	0.183		0.936		32.662		44.084	
	2	0.081		1.784	8.404		4.480	0.352		1.227		16.368		19.824	
	3	0.121		1.838	7.067		4.288	0.761		2.292		8.701		8.672	
Mean Diff.	1–2	−0.038	**	−0.355	−0.034		−0.137	−0.169	**	−0.292		16.294		24.259	*
	1–3	−0.079	***	−0.409	1.302		0.056	−0.578	***	−1.356	**	23.961	*	35.412	**
	2–3	−0.041	*	−0.054	1.336	***	0.193	−0.409	**	−1.064	**	7.667	*	11.152	*
Median	1	0.041		1.381	7.973		4.207	0.200		1.140		26.667		43.603	
	2	0.086		1.724	8.461		4.430	0.375		1.357		15.059		21.288	
	3	0.119		1.738	7.093		4.229	0.810		2.557		8.000		9.395	
SD	1	0.013		0.531	1.115		0.395	0.068		0.487		11.542		13.270	
	2	0.021		0.482	0.575		0.305	0.075		0.452		5.825		8.698	
	3	0.024		0.331	0.301		0.302	0.225		0.498		2.750		2.927	
Min.	1	0.028		0.820	7.553		3.871	0.070		0.149		23.273		27.625	
	2	0.050		1.150	7.231		4.111	0.226		0.176		8.533		8.760	
	3	0.082		1.451	6.538		3.942	0.466		1.510		4.655		3.571	
Max.	1	0.062		2.208	10.300		4.923	0.254		1.393		51.200		60.010	
	2	0.117		2.839	9.168		5.063	0.442		1.588		26.600		34.063	
	3	0.151		2.306	7.378		4.732	1.027		2.874		13.474		11.659	

Note. $N = 21$, $n_1 = 5$, $n_2 = 9$, $n_3 = 7$. *$p < .05$. **$p < .01$, ***$p < .001$. Multiple comparisons were corrected with Games-Howell method. Cluster 1 = immobile, 2 = anchored, 3 = dynamic.

vectors that explain 71% of the variation were chosen for the next step (see Fig. 3).

Based on the result of the WSS and gap statistic plot (see Fig. 4), we initiated K-means clustering with three clusters and 25 iterations to generate a classification. The K-means algorithm successfully differentiated three distinctive movement patterns. The quality of the clustering result was validated with a large Silhouette index of 0.85 and a small *S_Dbw* of 0.09. Therefore, according to the steps illustrated in Fig. 2, we successfully identified distinctive subgroups of preservice teachers based on their movement features.

We next inspected the characteristics of these clusters (numbered as clusters 1–3; C1–C3). First, we did not find any significant group differences by variables self-reported in the questionnaire including age, A-level grade, semester, self-rated classroom management and VR experience, self-rated preparedness for the task, self-efficacy in classroom management and cognitive load (see descriptives in Table A1). When all recorded fixations were examined, the group differences in fundamental eye movement metrics were likewise not significant: overall number of fixations ($n_{C1} = 1540$, $n_{C2} = 1677$, $n_{C3} = 1323$), average fixation duration in seconds ($M_{C1} = 0.87$, $SD_{C1} = 0.90$, $M_{C2} = 0.82$, $SD_{C2} = 0.91$, $M_{C3} = 0.84$, $SD_{C3} = 1.09$), and average gaze direction in degrees ($M_{C1} = 15.43$, $SD_{C1} = 1.45$, $M_{C2} = 16.04$, $SD_{C2} = 2.23$, $M_{C3} = 14.53$, $SD_{C3} = 1.82$).

Second, the overall movement characteristics of each cluster were examined. From initial visual examination (Fig. 5), C3 appeared to have more dispersed locations (points less aggregated) across the classroom compared to C1 and C2. C3 also moved to the back rows more often, while C1 and C2 stayed mostly in the front section. We then compared the eight summary statistics of movement features through multiple comparison (Table 3). The results were consistent with the initial visual inspection. To start, C3 had significantly larger *CE* than C1 ($t(9.4) = -7.36$, $p < .001$) and C2 ($t(12) = -3.54$, $p = .011$), which denoted less point aggregation and stronger dispersion of locations visited. This means the distribution of locations was less clumped and more separated, with longer distances in between. The size of point clusters did not differ significantly among the three groups, meaning that there was no evidence that teachers differed in the ranges of physical locations visited. On average, C3 had greater distances between fixation location and physical location in the classroom (dist_em_m) than C1 ($t(4.4) = 2.55$, $p = .044$) and C2 ($t(12.56) = 6.00$, $p < .001$), meaning that C3 looked at events that were further away from where they were standing, i.e., their immediate peripersonal spaces. Next, C3 had greater distances between consecutive locations (dis_loc_m) than C1 ($t(7.4) = -6.40$, $p < .001$) and C2 ($t(7) = -4.61$, $p = .006$). C3 seemed to be “jumping around” to points further away in the room than the other two clusters. Finally, C3 spent significantly shorter periods of time in one place (dwe_dur_m) than C1 ($t(4.3) = 4.55$, $p = .019$) and C2 ($t(11.9) = 3.48$, $p = .012$).

Based on these unique characteristics, we designated the movement patterns of the three clusters as immobile (C1), anchored (C2), and dynamic (C3). In summary, immobile teachers restricted their movement to the area behind the teacher’s desk and rarely ventured out to other locations in the classroom. Anchored teachers visited different locations but spent most of their time at the very front of the classroom. Dynamic teachers were found to have an overall more dispersed distribution of locations. They went to locations that were further away from the teacher’s desk, fixed their gaze on points that were further from where they were standing, and moved around the classroom to places that were further apart, spending much less time overall in any one location.

3.2. RQ2: *Movement Patterns and Visual Attention Performance*

After we identified three distinctive clusters of preservice teachers who had unique movement features, we then examined subgroups’ visual attention performance of the subgroups. Again, visual attention performance was operationalized as three measures: the number of fixations on each student disruption as they unfold, the time to first fixate and the total duration of fixations on such disruption.

First, none of the self-reported constructs (see Table A1 for descriptions) besides classroom management self-efficacy and perceived

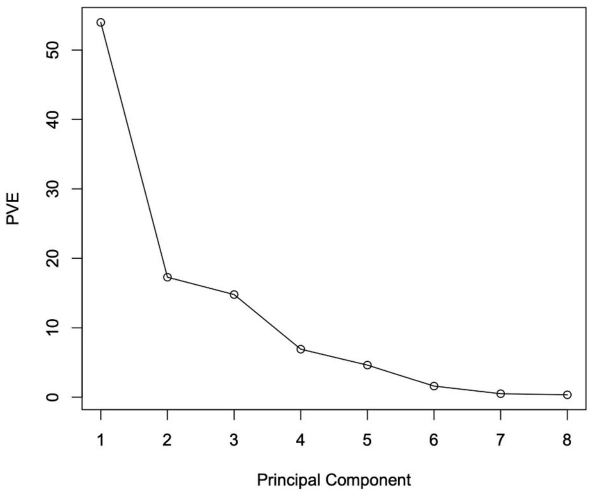

Fig. 3. Proportion of Variance Explained (PVE) Plot Against Each Principal Component. *Note.* The elbow appeared after the second principal component, which indicated a notable decrease in the variance explained by more than two principal components.

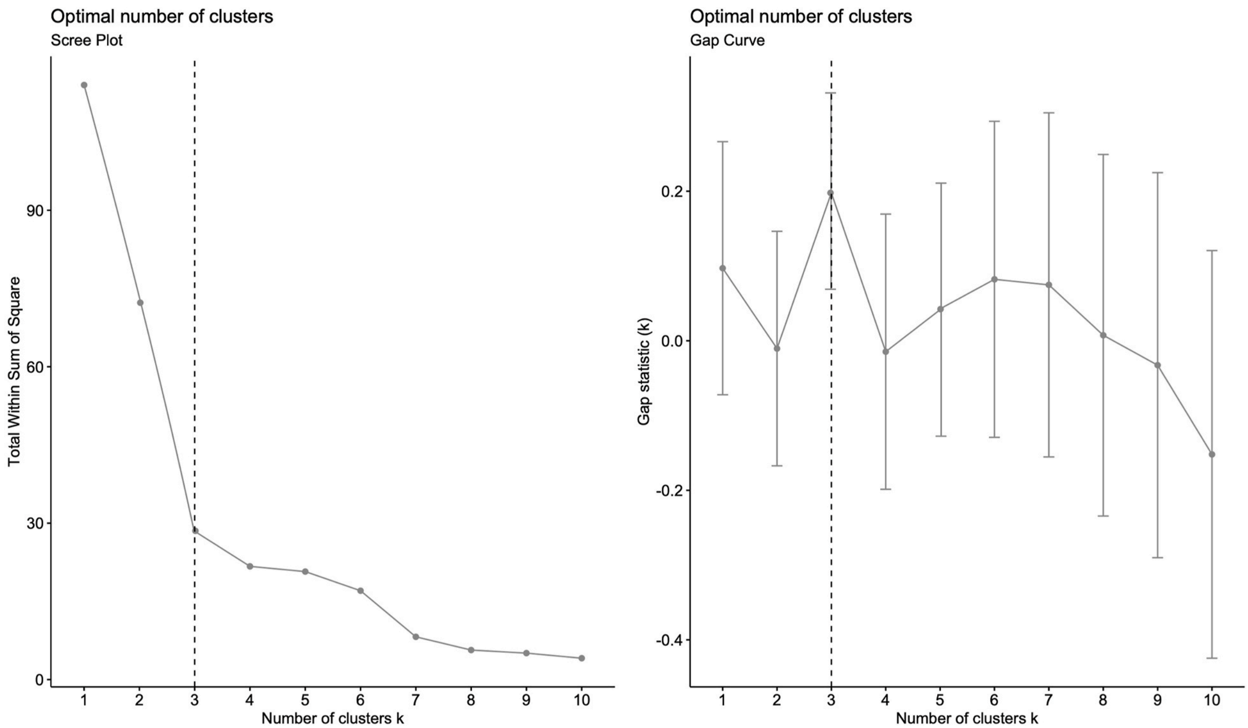

Fig. 4. Scree Plots f Total Within Sum of Square (WSS) and Gap Statistic.

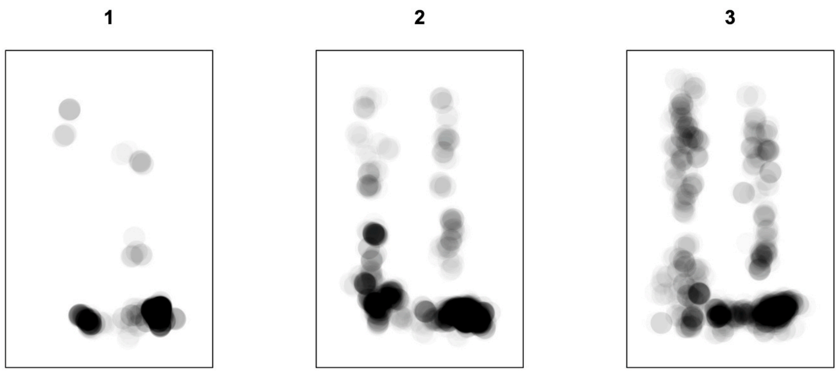

Fig. 5. Location Distribution Separated by Cluster Assignment. *Note.* $N = 21$, $n_1 = 5$, $n_2 = 9$, $n_3 = 7$. Each dot represents a teacher's location sampled at each second. The dots in each rectangle represent locations of all teachers in that cluster. The bottom of the rectangle is the front of the classroom. Cluster 1 = immobile, 2 = anchored, 3 = dynamic. For more details of the room map, see Fig. 1.

cognitive load were significantly correlated with the three visual attention performance measures. Self-efficacy in classroom management was significantly correlated with number of fixations ($r = 0.09$, $p = .006$) and fixation speed ($r = -0.12$, $p < .001$). Perceived cognitive load was also significantly correlated with number of fixations ($r = -0.08$, $p = .02$) and fixation speed ($r = 0.10$, $p = .005$). These covariates were used to construct the LMM model for evaluating the effect of cluster assignment as well as covariates on visual attention performance.

As shown in the model summary in Table 4, the dynamic pattern subgroup had significantly better visual attention performance than the immobile and anchored subgroups: The dynamic subgroup had a significantly higher number of fixations on each student disruption ($M_{C1} = 0.61$, $SD_{C1} = 1.05$, $M_{C2} = 0.69$, $SD_{C2} = 1.10$, $M_{C3} = 1.01$, $SD_{C3} = 1.26$); significantly faster fixation speed (time to first fixation in seconds) on each disruption ($M_{C1} = 12.63$, $SD_{C1} = 4.08$, $M_{C2} = 12.18$, $SD_{C2} = 4.25$, $M_{C3} = 11.42$, $SD_{C3} = 4.17$), as well as significantly longer total fixation durations (in seconds) on each disruption ($M_{C1} = 0.55$, $SD_{C1} = 1.35$, $M_{C2} = 0.64$, $SD_{C2} = 1.28$, $M_{C3} = 0.93$, $SD_{C3} = 1.73$). These effects are illustrated in Figs. 6–8. A post hoc analysis showed no significant differences in visual attention performance between immobile and anchored patterns.

In terms of the covariates, we found that only participant's perceived cognitive load of the teaching task in IVR was significantly

Table 4
Summary of the Linear Mixed-Effects Model of Visual Attention Performance.

	Number of fixations					Time to first fixation					Fixation duration				
Terms	$\hat{\beta}$	SE ($\hat{\beta}$)	*df*	*t*		$\hat{\beta}$	SE ($\hat{\beta}$)	*df*	*t*		$\hat{\beta}$	SE ($\hat{\beta}$)	*df*	*t*	
Cluster 1–2	0.030	0.103	836	0.293		0.061	0.38	836	0.160		0.042	0.132	836	0.316	
Cluster 1–3	−0.380	0.100	836	−3.797	***	1.043	0.369	836	2.824	*	−0.402	0.128	836	−3.127	**
Cluster 2–3	−0.410	0.097	836	−4.221	***	0.982	0.359	836	2.739	*	−0.444	0.125	836	−3.555	***
Self-efficacy	0.034	0.097	836	0.353		−0.531	0.358	836	−1.485		−0.211	0.124	836	−1.693	
Cognitive load	−0.066	0.025	836	−2.602	**	0.198	0.093	836	2.128	*	−0.080	0.032	836	−2.478	**

Note. Cluster 1 = immobile, 2 = anchored, 3 = dynamic. $^{*}p < .05$. $^{**}p < .01$, $^{***}p < .001$.

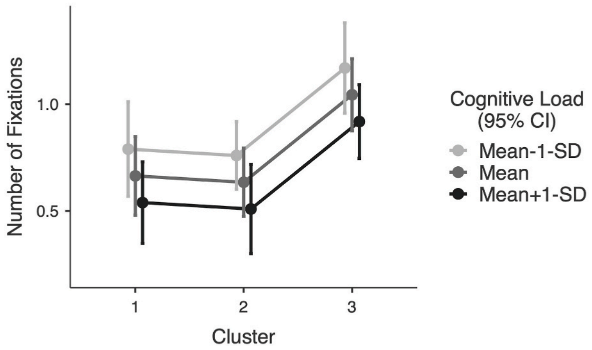

Fig. 6. Estimated Marginal Means of Number of Fixations Predicted by Cluster. *Note.* Y-axis is the total number of fixations on a disruption. Cluster 1 = immobile, 2 = anchored, 3 = dynamic. Error bars represent 95% confidence intervals.

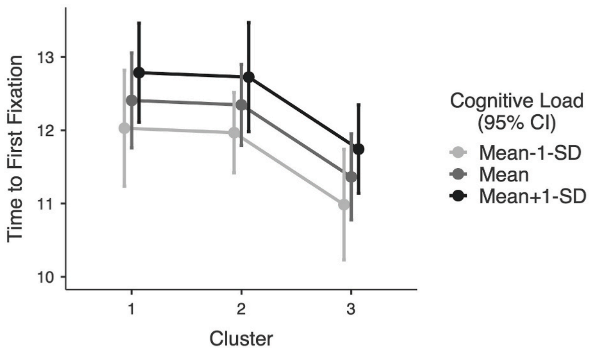

Fig. 7. Estimated Marginal Means of Time to First Fixation Predicted by Cluster. *Note.* Y-axis is the time to first fixate on a disruption. Cluster 1 = immobile, 2 = anchored, 3 = dynamic. Error bars represent 95% confidence intervals.

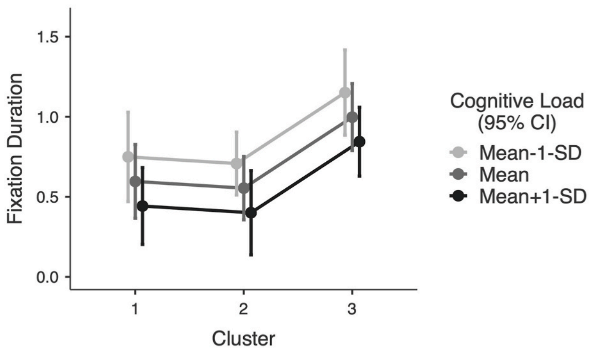

Fig. 8. Estimated Marginal Means of Fixation Duration Predicted by Cluster. *Note.* Y-axis is the total durations of all fixations on a disruption. Cluster 1 = immobile, 2 = anchored, 3 = dynamic. Error bars represent 95% confidence intervals.

and negatively associated visual attention performance measures: higher cognitive load was related to lower number of fixations ($\widehat{\beta} = -0.07$, $t(836) = -2.60$, $p = .009$), longer time to first fixation ($\widehat{\beta} = 0.20$, $t(836) = 2.13$, $p = .009$), and shorter fixation duration ($\widehat{\beta} = -0.08$, $t(836) = -2.48$, $p = .013$) on disruptions (see Figs. 6–8).

4. Discussion

The results of the present study demonstrate that there are indeed unique and differentiable movement patterns among preservice teachers. Based on K-means clustering of spatial point process statistics, we were able to identify three movement patterns with increasing levels of dispersion, which we labeled immobile (C1), anchored (C2), and dynamic (C3) movement patterns. Immobile teachers rarely leave their desks to other areas of the classroom. Although anchored teachers do move left and right, they primarily remain at the front of the classroom. In contrast, dynamic teachers disperse their presence more evenly throughout the classroom, moving frequently to distant locations, looking at locations further away from their standing positions, and spending less time in any one place. Among the three movement patterns, dynamic teachers were found to perform best at visually fixating on disruptions selectively (number and duration of fixations) and at doing so in a timely fashion (fixation speed) after controlling for confounding variables including expertise level, classroom environment and events, and teacher's demographic background. Furthermore, we observed that teachers who reported a high level of cognitive load had lower visual attention performances.

Why was the dynamic movement pattern associated with better visual attention performance? One possible explanation comes from the research on spatial attention, which differentiates between overt attention—where one's eyes move towards and remain fixated on a target—and covert attention—where attention is directed toward something on the periphery without actually fixating on it (Carrasco, 2011). Covert attention is a means of monitoring the environment and informing subsequent eye movements (overt attention) toward relevant events—for example, a student's sudden misbehavior in the classroom. As covert attention can be directed to more than one spot in parallel (Lamy & Tsal, 2001), activation of covert attention often leads to faster detection of a visual stimulus (Koivisto et al., 2004). When navigating a space, people generally deploy covert attention to their surroundings: They scan their environment without fixating on particular objects (Franchak & Adolph, 2010). In the teaching context, a dynamic movement pattern means more attempts to navigate the classroom, which will likely necessitate more active, covert attention to monitor the environment and a higher likelihood of detecting the disruption.

Another possible explanation stems from the research on visuomotor control, especially the investigation of peripersonal space. Visual processing is biased towards objects and events that occur near the body (McManus & Thomas, 2020), leading to better visual attention performance (Brozzoli et al., 2014). The reach of peripersonal space is subject to the influence of training (Thomas, 2017). For instance, the peripersonal space around a person's hands could extend to the adjacent space of hand-held tools when the individual has undergone training and practice in the tools' use (McManus & Thomas, 2020). Peripersonal space can also be extended through movements. Noel et al. (2015) compared participants' peripersonal spaces when standing still versus walking on a treadmill and found that this space was extended from about 65 cm when standing still to about 165 cm while walking. Dynamic teachers who move about more actively may therefore have a larger peripersonal space, allowing them to be sensitive to changes in larger areas.

The discovery that the dynamic movement pattern is associated with the best visual attention performance has significant implications for the understanding of teacher-student interactions and instructional quality. Researchers were aware as early as the 1970s that teachers engage more with students seated at the front and center of the classroom (Adams & Biddle, 1970). This *action zone* dominates the majority of teacher's attention (Smidekova et al., 2020) and communications with students (Jones, 1990). Students in the action zone also exhibit higher achievement (Montello, 1988), better learning outcomes (Blume et al., 2019), and more positive attitudes toward the teacher (Stires, 1980). The classrooms sampled in these studies had the traditional grid layout that discouraged teachers' free movement away from the front of the classroom, resulting in a consistently T-shaped action zone. The focus of the studies was primarily on this seating arrangement, rather than on the teacher's movement.

Our findings suggest that the action zone is not a static region within the classroom or a fixed group of students but a dynamically changing space around the teachers' bodies, akin to the conceptualization of peripersonal space. More dynamic movement in the classroom may easily break down the T-shaped action zone and allow the teacher to better engage with and support more students.

The current study also attempted to fill a gap in the research on teachers' professional development. Movement has often been considered an auxiliary behavioral measure that provides little information on the instructional process. Yet we found that preservice teachers exhibit unique movement patterns that are closely related to their visual attention performance, indicating a need for differentiated support for teachers based on their movement patterns—especially those with an immobile movement pattern. Since teachers can be classified based on the features of their movement during a short instructional task, this result could be used in the future to train classifiers for the autoclassification of movement patterns.

The additional finding that high cognitive load was negatively associated with all three metrics for visual attention performance corresponds with previous findings that cognitive load can be reliably measured through eye tracking (e.g., Duchowski et al., 2018; Wang et al., 2014; Zu et al., 2020). For instance, studies have shown that lower mental effort and cognitive processing is associated with shorter fixation durations on stimulus (Nuthmann & Henderson, 2012) Our finding demonstrated the potential for eye tracking in IVR to function as a sensitive, non-invasive measure of cognitive load in realistic teaching scenarios. This could inform the development of interventions aimed at managing cognitive load, thereby enabling teachers to maintain optimal visual attention focus during their everyday work.

Finally, the present study showcases that the potential of IVR classroom extends beyond teacher training. As a configurable environment, the IVR classroom has established itself as a uniquely suited experimental testbed for both teacher and student behaviors (Blume et al., 2019; Huang et al., 2021, 2022). The present study builds on previous evidence, showing the usefulness of IVR in collecting process-based, low-inference measures that provide rich and unbiased insight into teachers' experience.

4.1. Limitations and Future Directions

One limitation of this study is that it did not find any a priori variables linked to the movement patterns identified, including preservice teachers' experience in classroom management. Individual traits such as personality have been shown to be related to movement patterns (e.g., Ai et al., 2019; Götz et al., 2020; Oishi & Choi, 2020). A valuable direction for future research would therefore be to examine whether extroverted teachers exhibit more dynamic movement patterns. An additional pertinent aspect to consider is the differentiated emphasis of preservice teachers on various aspects of instruction, such as prioritizing classroom management versus delivering lectures. If a preservice teacher were to prioritize the presentation aspect of their work, they may position themselves in closer proximity to the projection screen, resulting in reduced visual attention towards students' behaviors. Future research that evaluates the teacher's emphasis during instruction will be useful in gaining a deeper understanding of the individual differences in visual attention performance during instruction.

As the sample included only preservice teachers who had not taught in real-life classrooms, the relationship between expertise level and movement pattern as well as their joint influence on visual attention performance is not yet known. Given that expert teachers usually perform better in visual attention than novice teachers, it would be intriguing to examine whether more experienced teachers move in a different way than novice ones.

Given the correlational nature of this investigation, it is not yet possible to claim whether one movement pattern is superior to others. Therefore, our results do not directly lead to inferences about possible interventions. Further experiments would be needed to substantiate the potential casual relationships between movement patterns and visual attention performance to answer whether we should explicitly cultivate certain movement patterns. Furthermore, causal research will enable the investigation of whether the relationship between movement pattern and visual attention performance is moderated by high-level factors pertaining not only to perceiving disruptions, but also to reasoning and interpreting them to achieve "withitness"—the ability to maintain a continuous awareness of classroom events and communicate this awareness to students (Kounin, 1970). This proposed research direction holds significant promise as it will facilitate understanding and analyzing the complex cognitive processes involved in teachers' professional vision.

In the current study, teachers' physical movement was depicted as a two-dimensional point process that captures their macro-motion. Due to the limitations of motion tracking in IVR, we did not measure the micro-motion, especially body rotation on a vertical axis, which might also be highly relevant for teacher's visual attention. For the dynamic movement pattern to be advantageous for noticing classroom events, for instance, teachers should also demonstrate head movement or rotate their bodies along the vertical axis to avoid their students from being positioned behind them. External validation from physical reality is also needed to substantiate the current findings about preservice teachers' movement patterns and visual attention performance. This is particularly crucial given that the users can move with teleportation inside the IVR environment which is not natural in physical reality. With more wearable motion trackers readily available, collecting process-based movement data from real-life classrooms is now attainable.

Although the present study has made valuable strides in understanding the teacher's in-situ visual attention performance, we also relied on a specific operationalization of visual attention performance which may not encapsulate the full range of visual behaviors that occur in a classroom setting. In future research, it would be beneficial to investigate different operationalization schemes, including diverse eye movement measures (e.g., refixations, pupil size, blink rate), to develop a more comprehensive understanding of teacher's visual attention.

4.2. Conclusions

The present study is the first in the field to quantitively distinguish the unique characteristics and patterns of teachers' body movement using IVR technology. We found that not only are there prominent individual differences in how preservice teachers move around the classroom; these movement patterns are also significantly associated with teachers' actual visual attention performance after controlling for confounding variables such as expertise level, classroom environment and events, and teacher demographic background. The dynamic movement pattern that showed the best visual attention performance was signified by more evenly distributed locations, longer travel distance, and less time in one place. Overall, this study advances theoretical knowledge about teachers' visual cognition and instructional behavior in realistic classroom situations based on its novel data collection method (standardized IVR classroom) and data sources (the combination of eye movement and movement data).

Credit author statement

Yizhen Huang: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing-Original Draft, Visualization; Eric Richter: Conceptualization, Investigation, Resources, Data Curation, Writing-Review & Editing; Thilo Kleickmann: Conceptualization, Resources, Project administration, Writing-Review & Editing; Katharina Scheiter: Conceptualization, Resources, Writing-Review & Editing; Dirk Richter: Conceptualization, Resources, Project administration, Writing-Review & Editing.

Declaration of competing interest

We declare that there are no known conflicts of interest associated with this research.

Data availability

Data will be made available on request.

Appendix A

Table A1
Questionnaire Items and Descriptives

Construct	Item	*M/SD* (missing)	Range (scale range)
Age	How old are you?	22.20/3.85 (1)	18–33
A-level grade	Please indicate your A-level (high school) grade point average—for instance, 2.3.	2.07/0.63 (2)	1.0–3.1 (1.0–4.0)
Semester of study	What semester of your teaching degree program are you in?	4.29/3.24	1–12
Classroom management experience	How many classroom management courses have you taken so far (including courses covering classroom management alongside other topics)?	1.05/0.92	0–3
VR experience	What experience do you have with virtual reality?	1.25/0.44 (1)	1–2 (1 = none; 3 = a lot)
Preparedness	How intensively did you prepare for the exercise?	3.24/1.18	1–5 (1 = not at all; 7 = very intense)
Classroom management self-efficacy	I know different routines or rituals to bring calm to the classroom. I am confident that I can control disruptive behavior in class. I can get students to follow rules in class. I can get a loud, disruptive student to be quiet. I am confident that I can manage not to let a few disruptive students ruin an entire lesson.	2.57/0.47	1.20–3.00 (1 = does not apply at all; 4 = fully applies)
Perceived cognitive load	Please rate your invested mental effort during the teaching task.	5.14/1.91	1–9 (1 = very low mental effort; 9 = very high mental effort)

Note. N = 21.

Table A2
Summary of Principal Component Analysis

	Eigenvalue	Percentage of variance	Cumulative percentage of variance
Component 1	4.319	53.982	53.982
Component 2	1.383	17.283	71.265
Component 3	1.183	14.783	86.048
Component 4	0.553	6.913	92.961
Component 5	0.370	4.621	97.582
Component 6	0.127	1.592	99.174
Component 7	0.039	0.491	99.665
Component 8	0.027	0.335	100.000

Appendix B

Dimension Reduction with PCA

The motivation of PCA-guided dimension reduction is to perform K-means clustering on only a few principal component score vectors instead of the entire feature space. Both scree plot and the rule of thumb were commonly used to decide the PCA components retained (Hastie et al., 2001). A scree plot that displays the percentage of variance explained (PVE) by each principal component against the number of principal components could be used to detect the turning point (the *elbow*) at which the marginal increase in explained variance begins to taper off. Therefore, this turning point could be the number of PCA components to retain in the feature space. On the other hand, the rule of thumb approach suggests retaining components that cumulatively explain a significant portion (70–90%) of the variance (Jolliffe & Cadima, 2016). The conjunction of these two methods decided the number of PCA components to retain for performing the K-means clustering.

K-Means Clustering Initiation

The scree plot of the total within sum of squares (WSS) and the gap statistic are two widely accepted methods of estimating an optimal K-means clustering initiation number. The WSS scree plot is similar to the scree plot of PVE: the potential number of clusters was plotted against the intra-cluster dissimilarity measure—the total within sum of squares (WSS). The number of clusters was determined by locating the elbow from which adding another cluster does not markedly reduce the WSS (Hastie et al., 2001). Another widely used data-driven method to optimize K-means initiation is gap statistic (Tibshirani et al., 2001). The gap refers to the difference between the observed and expected values of log WSS. The optimal number of clusters is estimated to maximize this gap.

Calculation of Fixation Location in IVR

The typical way of determining fixation location in IVR is the ray-casting method (Chen & Hou, 2022; Mansouryar et al., 2016). To determine where in the virtual world a user is looking at, gaze ray-casting method utilizes the combined data of the user's head position, head orientation, and gaze direction from each frame (Alghamdi & Alhalabi, 2019; Hasenbein et al., 2022). Specifically, a head direction vector linearly interpolated to 250 Hz and the associated gaze direction vector relative to the virtual world are used to locate the intersection point with the reconstructed virtual world, which represents the fixation location in relation to the virtual world (Anderson et al., 2021).

References

Abrams, R. A., Davoli, C. C., Du, F., Knapp, W. H., & Paull, D. (2008). Altered vision near the hands. *Cognition, 107*(3), 1035–1047. https://doi.org/10.1016/j.cognition.2007.09.006

Adams, R. S., & Biddle, B. J. (1970). *Realities of teaching: Explorations with video tape*. Holt, Rinehart and Winston.

Adolph, K. E., & Franchak, J. M. (2017). The development of motor behavior. *c, 8*(1–2), Article e1430. https://doi.org/10.1002/wcs.1430

Aggarwal, J. K., & Cai, Q. (1999). Human motion analysis: A review. *Computer Vision and Image Understanding, 73*(3), 428–440. https://doi.org/10.1006/cviu.1998.0744

Ai, P., Liu, Y., & Zhao, X. (2019). Big five personality traits predict daily spatial behavior: Evidence from smartphone data. *Personality and Individual Differences, 147*, 285–291. https://doi.org/10.1016/j.paid.2019.04.027

Albus, P., Vogt, A., & Seufert, T. (2021). Signaling in virtual reality influences learning outcome and cognitive load. *Computers & Education, 166*, Article 104154. https://doi.org/10/gh3s54.

Alghamdi, N., & Alhalabi, W. (2019). Fixation detection with ray-casting in immersive virtual reality. *International Journal of Advanced Computer Science and Applications, 10*(7). https://doi.org/10.14569/IJACSA.2019.0100710. Article 7.

Aloe, A. M., Amo, L. C., & Shanahan, M. E. (2014). Classroom management self-efficacy and burnout: A multivariate meta-analysis. *Educational Psychology Review, 26*(1), 101–126. https://doi.org/10/gn3s65.

Andersen, M. S., & Makransky, G. (2021). The validation and further development of a multidimensional cognitive load scale for virtual environments. *Journal of Computer Assisted Learning, 37*(1), 183–196. https://doi.org/10.1111/jcal.12478

Anderson, N., Jacobs, O., Bischof, W., & Kingstone, A. (2021). A natural look at scanpath theory: The way we move our head and eyes predicts scene recognition. *Journal of Vision, 21*(9), 2222. https://doi.org/10.1167/jov.21.9.2222

Armougum, A., Orriols, E., Gaston-Bellegarde, A., Marle, C. J.-L., & Piolino, P. (2019). Virtual reality: A new method to investigate cognitive load during navigation. *Journal of Environmental Psychology, 65*, Article 101338. https://doi.org/10.1016/j.jenvp.2019.101338

Baceviciute, S., Lucas, G., Terkildsen, T., & Makransky, G. (2022). Investigating the redundancy principle in immersive virtual reality environments: An eye-tracking and EEG study. *Journal of Computer Assisted Learning, 38*(1), 120–136. https://doi.org/10.1111/jcal.12595

Baddeley, A., Rubak, E., & Turner, R. (2016). *Spatial point patterns: Methodology and applications with R*. CRC Press, Taylor & Francis Group.

Bailey, J. O., & Bailenson, J. N. (2017). Immersive virtual reality and the developing child. In F. C. Blumberg, & P. J. Brooks (Eds.), *Cognitive development in digital contexts* (pp. 181–200). Academic Press. https://doi.org/10.1016/B978-0-12-809481-5.00009-2.

Ballard, D. H., Hayhoe, M. M., & Pelz, J. B. (1995). Memory representations in natural tasks. *Journal of Cognitive Neuroscience, 7*(1), 66–80. https://doi.org/10.1162/jocn.1995.7.1.66

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W.H. Freeman and Company.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Behets, D. (1997). Comparison of more and less effective teaching behaviors in secondary physical education. *Teaching and Teacher Education, 13*(2), 215–224. https://doi.org/10.1016/S0742-051X(96)00015-7

Blömeke, S., Gustafsson, J.-E., & Shavelson, R. J. (2015). Beyond dichotomies: Competence viewed as a continuum. *Zeitschrift für Psychologie, 223*(1), 3–13. https://doi.org/10.1027/2151-2604/a000194

Blömeke, S., Jentsch, A., Ross, N., Kaiser, G., & König, J. (2022). Opening up the black box: Teacher competence, instructional quality, and students' learning progress. *Learning and Instruction, 79*, Article 101600. https://doi.org/10.1016/j.learninstruc.2022.101600

Blume, F., Göllner, R., Moeller, K., Dresler, T., Ehlis, A.-C., & Gawrilow, C. (2019). Do students learn better when seated close to the teacher? A virtual classroom study considering individual levels of inattention and hyperactivity-impulsivity. *Learning and Instruction, 61*, 138–147. https://doi.org/10.1016/j.learninstruc.2018.10.004

Borko, H. (2016). Methodological contributions to video-based studies of classroom teaching and learning: A commentary. *ZDM, 48*(1), 213–218. https://doi.org/10.1007/s11858-016-0776-x

Brozzoli, C., Ehrsson, H. H., & Farnè, A. (2014). Multisensory representation of the space near the hand: From perception to action and interindividual interactions. *The Neuroscientist, 20*(2), 122–135. https://doi.org/10.1177/1073858413511153

Bufacchi, R. J., & Iannetti, G. D. (2018). An action field theory of peripersonal space. *Trends in Cognitive Sciences, 22*(12), 1076–1090. https://doi.org/10.1016/j.tics.2018.09.004

Carrasco, M. (2011). Visual attention: The past 25 years. *Vision Research, 51*(13), 1484–1525. https://doi.org/10.1016/j.visres.2011.04.012

Carrasco, M. (2018). How visual spatial attention alters perception. *Cognitive Processing, 19*(1), 77–88. https://doi.org/10.1007/s10339-018-0883-4

Charness, N., Reingold, E. M., Pomplun, M., & Stampe, D. M. (2001). The perceptual aspect of skilled performance in chess: Evidence from eye movements. *Memory & Cognition, 29*(8), 1146–1152. https://doi.org/10.3758/BF03206384

Chen, C. (2022). Immersive virtual reality to train preservice teachers in managing students' challenging behaviours: A pilot study. *British Journal of Educational Technology, 53*(4), 998–1024. https://doi.org/10.1111/bjet.13181

Chen, X., & Hou, W. (2022). *Identifying fixation and saccades in virtual reality*. arXiv:2205.04121). arXiv http://arxiv.org/abs/2205.04121.

Clark, P. J., & Evans, F. C. (1954). Distance to nearest neighbor as a measure of spatial relationships in populations. *Ecology, 35*(4), 445–453. https://doi.org/10.2307/1931034

Clarridge, P. B., & Berliner, D. C. (1991). Perceptions of student behavior as a function of expertise. *Journal of Classroom Interaction, 26*(1), 1–8.

Clay, V., König, P., & König, S. U. (2019). Eye tracking in virtual reality. *Journal of Eye Movement Research, 12*(1). https://doi.org/1614423976.

Costantini, M., Ambrosini, E., Tieri, G., Sinigaglia, C., & Committeri, G. (2010). Where does an object trigger an action? An investigation about affordances in space. *Experimental Brain Research, 207*(1), 95–103. https://doi.org/10.1007/s00221-010-2435-8

Dodge, S., Weibel, R., & Lautenschütz, A.-K. (2008). Towards a taxonomy of movement patterns. *Information Visualization, 7*(3–4), 240–252. https://doi.org/10.1057/palgrave.ivs.9500182

Doyle, W. (1977). Learning the classroom environment: An ecological analysis. *Journal of Teacher Education, 28*(6), 51–55. https://doi.org/10.1177/002248717702800616

Doyle, W. (2006). Ecological approaches to classroom management. In C. M. Evertson, & C. S. Weinstein (Eds.), *Handbook of classroom management. Research, practice, and contemporary issues* (pp. 97–126). Lawrence Erlbaum Associates.
Duchowski, A. T., Krejtz, K., Krejtz, I., Biele, C., Niedzielska, A., Kiefer, P., Raubal, M., & Giannopoulos, I. (2018). The index of pupillary activity: Measuring cognitive load *vis-à-vis* task difficulty with pupil oscillation. In *Proceedings of the 2018 CHI conference on human factors in computing systems* (pp. 1–13). https://doi.org/10.1145/3173574.3173856
Dye, M. W. G., & Bavelier, D. (2010). Differential development of visual attention skills in school-age children. *Vision Research, 50*(4), 452–459. https://doi.org/10.1016/j.visres.2009.10.010
Endsley, M. R. (1988). Design and evaluation for situation awareness enhancement. *Proceedings of the Human Factors Society 32nd Annual Meeting, 32*, 97–101. https://doi.org/10.1177/154193128803200221
van Es, E. A., & Sherin, M. G. (2002). Learning to notice: Scaffolding new teachers' interpretations of classroom interactions. *Journal of Technology and Teacher Education, 10*(4), 571–596.
Foulsham, T., Walker, E., & Kingstone, A. (2011). The where, what and when of gaze allocation in the lab and the natural environment. *Vision Research, 51*(17), 1920–1931. https://doi.org/10.1016/j.visres.2011.07.002
Franchak, J. M., & Adolph, K. E. (2010). Visually guided navigation: Head-mounted eye-tracking of natural locomotion in children and adults. *Vision Research, 50*(24), 2766–2774. https://doi.org/10.1016/j.visres.2010.09.024
Gamer, M., & Hecht, H. (2007). Are you looking at me? Measuring the cone of gaze. *Journal of Experimental Psychology: Human Perception and Performance, 33*(3), 705–715. https://doi.org/10.1037/0096-1523.33.3.705
Gao, H., Bozkir, E., Hasenbein, L., Hahn, J.-U., Göllner, R., & Kasneci, E. (2021). Digital transformations of classrooms in virtual reality. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1–10). https://doi.org/10/gksmh8.
Geeraerts, K., Tynjälä, P., & Heikkinen, H. L. T. (2018). Inter-generational learning of teachers: What and how do teachers learn from older and younger colleagues? *European Journal of Teacher Education, 41*(4), 479–495. https://doi.org/10.1080/02619768.2018.1448781
Gegenfurtner, A., Gruber, H., Holzberger, D., Keskin, Ö., Lehtinen, E., Seidel, T., Stürmer, K., & Säljö, R. (2022). Towards a cognitive theory of visual expertise: Methods of inquiry. In *Re-theorizing learning and research methods in learning research*. Routledge.
Gegenfurtner, A., Lehtinen, E., Helle, L., Nivala, M., Svedström, E., & Säljö, R. (2019). Learning to see like an expert: On the practices of professional vision and visual expertise. *International Journal of Educational Research, 98*, 280–291. https://doi.org/10.1016/j.ijer.2019.09.003
Gold, B., & Holodynski, M. (2017). Using digital video to measure the professional vision of elementary classroom management: Test validation and methodological challenges. *Computers & Education, 107*, 13–30. https://doi.org/10.1016/j.compedu.2016.12.012
González, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. *Nature, 453*(7196), Article 7196. https://doi.org/10.1038/nature06958. Article.
González, J. A., Rodríguez-Cortés, F. J., Cronie, O., & Mateu, J. (2016). Spatio-temporal point process statistics: A review. *Spatial Statistics, 18*, 505–544. https://doi.org/10.1016/j.spasta.2016.10.002
Goodale, M. A. (1998). Visuomotor control: Where does vision end and action begin? *Current Biology, 8*(14), R489–R491. https://doi.org/10.1016/S0960-9822(98)70314-8
Götz, F. M., Yoshino, S., & Oshio, A. (2020). The association between walkability and personality: Evidence from a large socioecological study in Japan. *Journal of Environmental Psychology, 69*, Article 101438. https://doi.org/10.1016/j.jenvp.2020.101438
Gundel, E., Piro, J., Straub, C., & Smith, K. (2019). Self-efficacy in mixed reality simulations: Implications for preservice teacher education. *The Teacher Educator, 54*, 244–269. https://doi.org/10.1080/08878730.2019.1591560
Halkidi, M., & Vazirgiannis, M. (2001). Clustering validity assessment: Finding the optimal partitioning of a data set. *Proceedings 2001 IEEE International Conference on Data Mining*, 187–194. https://doi.org/10.1109/ICDM.2001.989517
Hamm, L. M., Mistry, K., Black, J. M., Grant, C. C., & Dakin, S. C. (2019). Impact of children's postural variation on viewing distance and estimated visual acuity. *Translational Vision Science & Technology, 8*(1), 16. https://doi.org/10.1167/tvst.8.1.16
Han, E. (2021). Integrating mobile eye-tracking and VSLAM for recording spatial gaze in works of art and architecture. *Technology|Architecture + Design, 5*(2), 177–187. https://doi.org/10.1080/24751448.2021.1967058
Hasenbein, L., Stark, P., Trautwein, U., Queiroz, A. C. M., Bailenson, J., Hahn, J.-U., & Göllner, R. (2022). Learning with simulated virtual classmates: Effects of social-related configurations on students' visual attention and learning experiences in an immersive virtual reality classroom. *Computers in Human Behavior, 133*, Article 107282. https://doi.org/10.1016/j.chb.2022.107282
Hastie, T., Friedman, J., & Tibshirani, R. (2001). *The elements of statistical learning*. New York: Springer. https://doi.org/10.1007/978-0-387-21606-5
Hayhoe, M. M. (2017). Vision and action. *Annual Review of Vision Science, 3*(1), 389–413. https://doi.org/10.1146/annurev-vision-102016-061437
Hayhoe, M. M., & Ballard, D. (2005). Eye movements in natural behavior. *Trends in Cognitive Sciences, 9*(4), 188–194. https://doi.org/10.1016/j.tics.2005.02.009
Hennig, C. (2020). *Fpc: Flexible procedures for clustering [Manual]*. https://CRAN.R-project.org/package=fpc.
Hollingworth, A., Schrock, G., & Henderson, J. M. (2001). Change detection in the flicker paradigm: The role of fixation position within the scene. *Memory & Cognition, 29*(2), 296–304. https://doi.org/10.3758/BF03194923
Holmes, N. P., & Spence, C. (2004). The body schema and multisensory representation(s) of peripersonal space. *Cognitive Processing, 5*(2), 94–105. https://doi.org/10.1007/s10339-004-0013-3
Huang, Y., Miller, K. F., Cortina, K. S., & Richter, D. (2023). Teachers' professional vision in action. *Zeitschrift Für Pädagogische Psychologie [German Journal of Educational Psychology], 37*(1–2), 122–139. https://doi.org/10.1024/1010-0652/a000313.
Huang, Y., Richter, E., Kleickmann, T., & Richter, D. (2022). Class size affects preservice teachers' physiological and psychological stress reactions: An experiment in a virtual reality classroom. *Computers & Education, 184*, 104503. https://doi.org/10.1016/j.compedu.2022.104503.
Huang, Y., Richter, E., Kleickmann, T., & Richter, D. (2023). Virtual reality in teacher education from 2010 to 2020. In K. Scheiter, & I. Gogolin (Eds.), *Bildung für eine digitale Zukunft [Education for a Digital Future]* (pp. 399–441). Springer Fachmedien. https://doi.org/10.1007/978-3-658-37895-0_16.
Huang, Y., Richter, E., Kleickmann, T., & Richter, D. (2023). Comparing video and virtual reality as tools for fostering interest and self-efficacy in classroom management: Results of a pre-registered experiment. *British Journal of Educational Technology, 54*(2), 467–488. https://doi.org/10.1111/bjet.13254.
Huang, Y., Richter, E., Kleickmann, T., Wiepke, A., & Richter, D. (2021). Classroom complexity affects student teachers' behavior in a VR classroom. *Computers & Education, 163*, 104100. https://doi.org/10.1016/j.compedu.2020.104100.
Illian, J., Penttinen, A., Stoyan, H., & Stoyan, D. (2007). *Statistical analysis and modelling of spatial point patterns*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470725160
Ivanová, L., Laco, M., & Benesova, W. (2022). Unsupervised clustering-based analysis of the measured eye-tracking data. In *Fourteenth International Conference on Machine Vision (ICMV 2021), 12084* (pp. 53–60). https://doi.org/10.1117/12.2623035.
Jacobs, V. R., Lamb, L. L. C., & Philipp, R. A. (2010). Professional noticing of children's mathematical thinking. *Journal for Research in Mathematics Education, 41*(2), 169–202. https://doi.org/10.5951/jresematheduc.41.2.0169
James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 103). New York: Springer. http://link.springer.com/10.1007/978-1-4614-7138-7.
Jogeshwar, A. K., & Pelz, J. B. (2021). GazeEnViz4D: 4-D gaze-in-environment visualization pipeline. *Procedia Computer Science, 192*, 2952–2961. https://doi.org/10.1016/j.procs.2021.09.067
Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical & Engineering Sciences, 374*(2065), Article 20150202. https://doi.org/10.1098/rsta.2015.0202
Jones, M. G. (1990). Action zone theory, target students and science classroom interactions. *Journal of Research in Science Teaching, 27*(7), 651–660. https://doi.org/10.1002/tea.3660270705

Kassambara, A., & Mundt, F. (2020). *Factoextra: Extract and visualize the results of multivariate data analyses [Manual]*. https://CRAN.R-project.org/package=factoextra.
Keller, L., Cortina, K. S., Müller, K., & Miller, K. F. (2022). Noticing and weighing alternatives in the reflection of regular classroom teaching: Evidence of expertise using mobile eye-tracking. *Instructional Science, 50*, 251–272. https://doi.org/10/gnswdn.
Kerr, G., Ruskin, H. J., Crane, M., & Doolan, P. (2008). Techniques for clustering gene expression data. *Computers in Biology and Medicine, 38*(3), 283–293. https://doi.org/10.1016/j.compbiomed.2007.11.001
Koivisto, M., Hyönä, J., & Revonsuo, A. (2004). The effects of eye movements, spatial attention, and stimulus features on inattentional blindness. *Vision Research, 44*(27), 3211–3221. https://doi.org/10.1016/j.visres.2004.07.026
König, J., Santagata, R., Scheiner, T., Adleff, A.-K., Yang, X., & Kaiser, G. (2022). Teacher noticing: A systematic literature review of conceptualizations, research designs, and findings on learning to notice. *Educational Research Review, 36*, Article 100453. https://doi.org/10.1016/j.edurev.2022.100453
Kosko, K. W., Heisler, J., & Gandolfi, E. (2022). Using 360-degree video to explore teachers' professional noticing. *Computers & Education, 180*, Article 104443. https://doi.org/10.1016/j.compedu.2022.104443
Kounin, J. S. (1970). *Discipline and group management in classrooms*. Holt, Rinehart & Winston.
Kyrlitsias, C., & Michael-Grigoriou, D. (2018). Asch conformity experiment using immersive virtual reality. *Computer Animation and Virtual Worlds, 29*(5), 1–16. https://doi.org/10.1002/cav.1804
Laasonen, M., Salomaa, J., Cousineau, D., Leppämäki, S., Tani, P., Hokkanen, L., & Dye, M. (2012). Project DyAdd: Visual attention in adult dyslexia and ADHD. *Brain and Cognition, 80*(3), 311–327. https://doi.org/10.1016/j.bandc.2012.08.002
Làdavas, E., Pellegrino, G. di, Farnè, A., & Zeloni, G. (1998). Neuropsychological evidence of an integrated visuotactile representation of peripersonal space in humans. *Journal of Cognitive Neuroscience, 10*(5), 581–589. https://doi.org/10.1162/089892998562988
Lamy, D., & Tsal, Y. (2001). On the status of location in visual attention. *European Journal of Cognitive Psychology, 13*(3), 305–342. https://doi.org/10.1080/09541440125789
Land, M., & Tatler, B. (2009). *Looking and acting: Vision and eye movements in natural behaviour*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198570943.001.0001
Leech, R. M., McNaughton, S. A., & Timperio, A. (2014). The clustering of diet, physical activity and sedentary behavior in children and adolescents: A review. *International Journal of Behavioral Nutrition and Physical Activity, 11*(1). https://doi.org/10.1186/1479-5868-11-4. Article 1.
Lê, S., Josse, J., & Husson, F. (2008). FactoMineR: A package for multivariate analysis. *Journal of Statistical Software, 25*(1), 1–18. https://doi.org/10.18637/jss.v025.i01
Liu, Y., Li, Z., Xiong, H., Gao, X., & Wu, J. (2010). Understanding of internal clustering validation measures. In *2010 IEEE international conference on data mining* (pp. 911–916). https://doi.org/10.1109/ICDM.2010.35
Makransky, G., Andreasen, N. K., Baceviciute, S., & Mayer, R. E. (2020). Immersive virtual reality increases liking but not learning with a science simulation and generative learning strategies promote learning in immersive virtual reality. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000473
Maloney, L. T., & Zhang, H. (2010). Decision-theoretic models of visual perception and action. *Vision Research, 50*(23), 2362–2374. https://doi.org/10.1016/j.visres.2010.09.031
Mansouryar, M., Steil, J., Sugano, Y., & Bulling, A. (2016). 3D gaze estimation from 2D pupil positions on monocular head-mounted eye trackers. In *Proceedings of the ninth biennial ACM symposium on eye tracking research & applications* (pp. 197–200). https://doi.org/10.1145/2857491.2857530
McGarr, O. (2021). The use of virtual simulations in teacher education to develop pre-service teachers' behaviour and classroom management skills: Implications for reflective practice. *Journal of Education for Teaching, 47*(2), 274–286. https://doi.org/10.1080/02607476.2020.1733398
McInerney, J., Stein, S., Rogers, A., & Jennings, N. R. (2013). Breaking the habit: Measuring and predicting departures from routine in individual human mobility. *Pervasive and Mobile Computing, 9*(6), 808–822. https://doi.org/10.1016/j.pmcj.2013.07.016
McIntyre, N. A., & Foulsham, T. (2018). Scanpath analysis of expertise and culture in teacher gaze in real-world classrooms. *Instructional Science, 46*(3), 435–455. https://doi.org/10.1007/s11251-017-9445-x
McKinney, T., Chajka, K., & Hayhoe, M. (2008). Pro-active gaze control in squash. *Journal of Vision, 8*(6), 111. https://doi.org/10.1167/8.6.111
McManus, R. R., & Thomas, L. E. (2020). Vision is biased near handheld, but not remotely operated, tools. *Attention, Perception, & Psychophysics, 82*(8), 4038–4057. https://doi.org/10.3758/s13414-020-02099-8
Mecca, G., Raunich, S., & Pappalardo, A. (2007). A new algorithm for clustering search results. *Data & Knowledge Engineering, 62*(3), 504–522. https://doi.org/10.1016/j.datak.2006.10.006
Miller, K. F. (2010). Situation awareness in teaching: What educators can learn from video-based research in other fields. In M. G. Sherin, V. Jacobs, & R. Philipp (Eds.), *Mathematics teacher noticing* (1st ed., pp. 51–65). Routledge.
Montello, D. R. (1988). Classroom seating location and its effect on course achievement, participation, and attitudes. *Journal of Environmental Psychology, 8*(2), 149–157. https://doi.org/10.1016/S0272-4944(88)80005-7
Müller, S. R., Peters, H., Matz, S. C., Wang, W., & Harari, G. M. (2020). Investigating the relationships between mobility behaviours and indicators of subjective well–being using smartphone–based experience sampling and GPS tracking. *European Journal of Personality, 34*(5), 714–732. https://doi.org/10.1002/per.2262
Noel, J.-P., Grivaz, P., Marmaroli, P., Lissek, H., Blanke, O., & Serino, A. (2015). Full body action remapping of peripersonal space: The case of walking. *Neuropsychologia, 70*, 375–384. https://doi.org/10.1016/j.neuropsychologia.2014.08.030
Nuthmann, A., & Henderson, J. M. (2012). Using CRISP to model global characteristics of fixation durations in scene viewing and reading with a common mechanism. *Visual Cognition, 20*(4–5), 457–494. https://doi.org/10.1080/13506285.2012.670142.
Oishi, S., & Choi, H. (2020). Personality and space: Introversion and seclusion. *Journal of Research in Personality, 85*, Article 103933. https://doi.org/10.1016/j.jrp.2020.103933
Paas, F. G. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology, 84*(4), 429–434. https://doi.org/10.1037/0022-0663.84.4.429
Parasuraman, R. (1986). Vigilance, monitoring, and search. In *, Vol. 2. Handbook of perception and human performance* (pp. 1–39). John Wiley & Sons. Cognitive processes and performance.
Patla, A., & Vickers, J. (2003). How far ahead do we look when required to step on specific locations in the travel path during locomotion? *Experimental Brain Research, 148*(1), 133–138. https://doi.org/10.1007/s00221-002-1246-y
Pfitzner-Eden, F. (2016). *Teacher's sense of efficacy scale (TSES)—German adapted version*. Open Test Archive: Leibniz-Institute for Psychology. https://doi.org/10.23668/PSYCHARCHIVES.6585
Pfitzner-Eden, F., Thiel, F., & Horsley, J. (2014). An adapted measure of teacher self-efficacy for preservice teachers: Exploring its validity across two countries. *Zeitschrift für Padagogische Psychologie, 28*(3), 83–92. https://doi.org/10.1024/1010-0652/a000125
Plass, J. L., Moreno, R., & Brünken, R. (Eds.). (2010). *Cognitive load theory*. Cambridge University Press.
R Core Team. (2021). *R: A language and environment for statistical computing (4.0.4)*. R Foundation for Statistical Computing. https://www.R-project.org/.
Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education, 147*, Article 103778. https://doi.org/10.1016/j.compedu.2019.103778
Reingold, E. M., Charness, N., Pomplun, M., & Stampe, D. M. (2001). Visual span in expert chess players: Evidence from eye movements. *Psychological Science, 12*(1), 48–55. https://doi.org/10.1111/1467-9280.00309
Richter, E., Hußner, I., Huang, Y., Richter, D., & Lazarides, R. (2022). Video-based reflection in teacher education: Comparing virtual reality and real classroom videos. *Computers & Education, 190*, 104601. https://doi.org/10.1016/j.compedu.2022.104601.
Rizzolatti, G., Fadiga, L., Fogassi, L., & Gallese, V. (1997). The space around us. *Science, 277*(5323), 190–191. https://doi.org/10.1126/science.277.5323.190
Salomon, G. (1984). Television is "easy" and print is "tough": The differential investment of mental effort in learning as a function of perceptions and attributions. *Journal of Educational Psychology, 76*(4), 647–658. https://doi.org/10.1037/0022-0663.76.4.647

Seidel, T., & Stürmer, K. (2014). Modeling and measuring the structure of professional vision in preservice teachers. *American Educational Research Journal, 51*(4), 739–771. https://doi.org/10.3102/0002831214531321

Seidel, T., Stürmer, K., Blomberg, G., Kobarg, M., & Schwindt, K. (2011). Teacher learning from analysis of videotaped classroom situations: Does it make a difference whether teachers observe their own teaching or that of others? *Teaching and Teacher Education, 27*(2), 259–267. https://doi.org/10/d4qvfx.

Seufert, C., Oberdörfer, S., Roth, A., Grafe, S., Lugrin, J.-L., & Latoschik, M. E. (2022). Classroom management competency enhancement for student teachers using a fully immersive virtual classroom. *Computers & Education, 179*, Article 104410. https://doi.org/10/gnw5bk.

Shadiev, R., & Li, D. (2023). A review study on eye-tracking technology usage in immersive virtual reality learning environments. *Computers & Education, 196*, Article 104681. https://doi.org/10.1016/j.compedu.2022.104681

Sherin, M. G., Jacobs, V. R., & Philipp, R. A. (Eds.). (2010). *Mathematics teacher noticing.* Routledge.

Sherin, M. G., & van Es, E. A. (2009). Effects of video club participation on teachers' professional vision. *Journal of Teacher Education, 60*(1), 20–37. https://doi.org/10.1177/0022487108328155

Slater, M. (2018). Immersion and the illusion of presence in virtual reality. *British Journal of Psychology, 109*(3), 431–433. https://doi.org/10.1111/bjop.12305

Smidekova, Z., Janik, M., Minarikova, E., & Holmqvist, K. (2020). Teachers' gaze over space and time in a real-world classroom. *Journal of Eye Movement Research, 13*(4). https://doi.org/10.16910/jemr.13.4.1. https://doi.org/1614421835.

Stahnke, R., & Blömeke, S. (2021). Novice and expert teachers' noticing of classroom management in whole-group and partner work activities: Evidence from teachers' gaze and identification of events. *Learning and Instruction, 74*, Article 101464. https://doi.org/10.1016/j.learninstruc.2021.101464

Stahnke, R., Schueler, S., & Roesken-Winter, B. (2016). Teachers' perception, interpretation, and decision-making: A systematic review of empirical mathematics education research. *ZDM, 48*(1), 1–27. https://doi.org/10.1007/s11858-016-0775-y

Star, J. R., & Strickland, S. K. (2008). Learning to observe: Using video to improve preservice mathematics teachers' ability to notice. *Journal of Mathematics Teacher Education, 11*(2), 107–125. https://doi.org/10.1007/s10857-007-9063-7

Stein, N., Niehorster, D. C., Watson, T., Steinicke, F., Rifai, K., Wahl, S., & Lappe, M. (2021). A comparison of eye tracking latencies among several commercial head-mounted displays. *I-Perception, 12*(1). https://doi.org/10.1177/2041669520983338, 2041669520983338.

Stires, L. (1980). Classroom seating location, student grades, and attitudes: Environment or self-selection? *Environment and Behavior, 12*(2), 241–254. https://doi.org/10.1177/0013916580122008

Stockero, S. L., Rupnow, R. L., & Pascoe, A. E. (2017). Learning to notice important student mathematical thinking in complex classroom interactions. *Teaching and Teacher Education, 63*, 384–395. https://doi.org/10.1016/j.tate.2017.01.006

Stürmer, K., Seidel, T., Müller, K., Häusler, J., & Cortina, K. S. (2017). What is in the eye of preservice teachers while instructing? An eye-tracking study about attention processes in different teaching situations. *Zeitschrift für Erziehungswissenschaft, 20*(1), 75–92. https://doi.org/10.1007/s11618-017-0731-9

Thomas, L. E. (2017). Action experience drives visual-processing biases near the hands. *Psychological Science, 28*(1), 124–131. https://doi.org/10.1177/0956797616678189

Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B, 63*(2), 411–423. https://doi.org/10.1111/1467-9868.00293

Tidbury, L. P., & O'Connor, A. R. (2015). Testing vision testing: Quantifying the effect of movement on visual acuity measurement. *Eye, 29*(1). https://doi.org/10.1038/eye.2014.247. Article 1.

Tobii. (2021). *Eye tracking performance assessment—for VR/AR headsets and wearables (whitepaper version 1.0; Tobii white paper)*. Tobii XR https://www.tobii.com/resource-center/reports-and-papers/eye-tracking-performance-assessment#cta-section.

Wang, Q., Yang, S., Liu, M., Cao, Z., & Ma, Q. (2014). An eye-tracking study of website complexity from cognitive load perspective. *Decision Support Systems, 62*, 1–10. https://doi.org/10.1016/j.dss.2014.02.007

Wolff, C. E., Jarodzka, H., & Boshuizen, H. P. A. (2020). Classroom management scripts: A theoretical model contrasting expert and novice teachers' knowledge and awareness of classroom events. *Educational Psychology Review*. https://doi.org/10.1007/s10648-020-09542-0

Wolff, C. E., Jarodzka, H., van den Bogert, N., & Boshuizen, H. P. A. (2016). Teacher vision: Expert and novice teachers' perception of problematic classroom management scenes. *Instructional Science, 44*(3), 243–265. https://doi.org/10.1007/s11251-016-9367-z

Xu, Q., Ding, C., Liu, J., & Luo, B. (2015). PCA-guided search for K-means. *Pattern Recognition Letters, 54*, 50–55. https://doi.org/10.1016/j.patrec.2014.11.017

Yuan, M. (2018). Human dynamics in space and time: A brief history and a view forward. *Transactions in GIS, 22*(4), 900–912. https://doi.org/10.1111/tgis.12473

Zargari Marandi, R., Madeleine, P., Omland, Ø., Vuillerme, N., & Samani, A. (2018). Reliability of oculometrics during a mentally demanding task in young and old adults. *IEEE Access, 6*, 17500–17517. https://doi.org/10.1109/ACCESS.2018.2819211

Zu, T., Hutson, J., Loschky, L. C., & Rebello, N. S. (2020). Using eye movements to measure intrinsic, extraneous, and germane load in a multimedia learning environment. *Journal of Educational Psychology, 112*(7), 1338–1352. https://doi.org/10.1037/edu0000441