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PAPER

Assessing Individual Differences in Mental Load: Eye-Tracking Insights for Adaptive Learning

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ABSTRACT

This study explores individual differences in working memory and perceptual load, with a particular focus on sex-related variations, to improve adaptive technology-enhanced learning. Using eye-tracking metrics, such as fixation duration and fixation rate, the research highlights how these measures can provide actionable insights for personalizing learning environments. The results reveal significant sex-related differences: females exhibited shorter fixation durations and higher fixation rates, reflecting elevated perceptual load, while males demonstrated longer fixation durations and greater efficiency in handling cognitively demanding tasks. These findings suggest that sex differences in cognitive processing influence task performance and engagement, underscoring the need to consider such variations in educational design. By integrating fixation-based metrics, TEL systems can adapt content dynamically to align with learners' cognitive profiles, fostering more inclusive and effective learning experiences. The study also advocates for training transferable skills, such as attention switching, to enhance learners' ability to manage perceptual load.

KEYWORDS

technology-enhanced learning, eye tracking, perceptual load, sex differences, adaptive learning.

1 INTRODUCTION

Technology-enhanced learning (TEL), also referred to as e-learning, focuses on integrating information and communication technologies (ICT) into educational practices to improve learning outcomes. The challenge for TEL systems is to design technologies that effectively enhance learning while developing methods to measure and evaluate this enhancement in terms of educational performance and outcomes [1], [2].

Technological advancements in TEL systems have introduced a wide array of tools to enrich learner experiences, including multimedia components such as spoken explanations, dynamic animations, simulations, and interconnected

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hypermedia environments [3]. These tools, along with virtual learning platforms and advanced online collaboration systems, hold significant potential to transform educational practices. However, decades of integrating innovative technologies into learning environments have revealed that the effectiveness of such tools depends more on their ability to engage learners and foster cognitive activities than on the technology itself [4], [5], [6]. While TEL can play a significant role in learning, its use alone may not always yield sufficient benefits to justify the investment in developing such tools. Specifically, TEL can place additional demands on learners' cognitive resources, potentially hindering the acquisition of new knowledge. Research into TEL has shown varied outcomes [3], underscoring the importance of analyzing the cognitive processes and structures involved to enhance the effectiveness of such learning environments.

Despite these findings, there remains a lack of a comprehensive model that integrates learner-specific characteristics—such as prior knowledge, working memory capacity, and domain-specific abilities—to predict the relative intrinsic difficulty of learning materials for individuals in specific contexts [7].

To address this gap, the present research investigates individual differences in mental load, with a particular focus on sex-based variations. In this paper, 'sex' is used to refer to biological differences. When referring to previous studies, the terminology used by the original authors is retained. It also explores available methods for measuring these differences, presents findings on sex-related differences in different types of load, and evaluates current technological solutions in TEL. The primary aim of this study is to examine how individual differences and mental load influence TEL design, with the potential to inform the development of effective e-learning and blended learning solutions.

1.1 Mental load in instructional design

The prevailing theory behind guiding the instructional design and evaluation of educational multimedia environments and web-based instruction is a cognitive load theory (CLT) [8], [9], [10]. CLT distinguishes between three types of cognitive load: intrinsic, extraneous, and germane. Intrinsic cognitive load is determined by the inherent complexity of the material to be learned and the interactivity of its elements, in combination with the learner's prior knowledge. This type of load is essential for achieving learning goals and cannot be altered by instructional design but must be carefully considered to ensure learners are not overwhelmed. In contrast, extraneous cognitive load arises from suboptimal instructional design that introduces unnecessary processing demands, such as redundant information or poorly structured materials. For instance, presenting an explanatory text alongside a self-explanatory diagram or providing redundant information to more knowledgeable learners can unnecessarily consume working memory resources, making them unavailable for meaningful learning [3]. Germane cognitive load, however, is associated with constructing, processing, and automating schemas. It supports learning by focusing attention on relevant cognitive processes and is influenced by factors such as learner motivation and engagement [3], [10]. While instructional design can enhance germane load, it is also subject to external factors, such as the professional skills of educators, which can negatively impact motivation. By carefully managing these three types of load, instructional designers and educators can create learning environments that optimize cognitive resources and enhance learning outcomes.

Researchers in cognitive load theory strive to optimize instructional design by managing cognitive load, ensuring that learners neither experience excessive nor insufficient load, as both extremes can negatively impact learning outcomes [11]. The goal is to achieve an optimal cognitive load that enhances learning by maximizing germane load, which supports schema construction, while minimizing extraneous load, which stems from irrelevant or poorly designed instructional elements that hinder learning. The impact of extraneous cognitive load varies depending on task complexity. When intrinsic cognitive load is low, extraneous load from instructional materials or the learning environment may have little effect on learning. However, for more complex tasks with high intrinsic load, managing extraneous load becomes crucial to prevent cognitive overload and ensure effective learning [12]. Distinguishing and measuring intrinsic, extraneous, and germane cognitive load is essential to understanding their unique contributions to the learning process.

According to [3], [13], extraneous cognitive load is influenced by instructional design factors, such as lecture format, user-friendly learning activities, and support for adapting to the learning environment. Leppink et al. [14] found that adjusting learning content to a more favorable format reduced intrinsic and extraneous load while increasing germane load, emphasizing the importance of adaptable content in learning systems. However, their study relied on subjective measures and included only a single posttest after both formats, making it unclear how each format individually affected performance. To address this limitation, the authors recommended that future research incorporate separate posttests for each format and combine subjective measures with biological metrics, such as eye tracking, to gain deeper insights. Despite advancements in cognitive load research, empirical studies continue to face challenges in isolating and distinguishing the effects of different cognitive load types in real-world learning environments [7], [10]. Addressing these challenges will be key to refining instructional strategies and improving learning outcomes.

To address this issue, we examined load theory of selective attention as proposed by Lavie and Dalton [15], which complements CLT. This theory emphasizes the role of working memory in maintaining priorities between targets and distractors during selective attention tasks. According to [15], distractors can be excluded from perception when the perceptual load of task-relevant stimuli is high enough to fully utilize perceptual capacity, leaving no room for processing irrelevant distractors. In contrast, under low perceptual load conditions, unused perceptual capacity may be directed toward processing irrelevant information. Thus, high perceptual load promotes early selection, filtering out distractors, while low perceptual load leads to late selection, allowing distractors to be processed. The interplay between perceptual load and working memory load reveals how much relevant and irrelevant information is processed during task performance [15]. Building on this foundation, Liu et al. [16] provided a practical perspective on applying load theory in educational contexts, emphasizing methods for assessing extraneous cognitive load and identifying its sources. In educational settings, high perceptual load may limit the processing of relevant information, forcing students to expend additional effort to fully comprehend teaching materials, thereby increasing extraneous cognitive load. Similarly, high working memory load can deplete a student's cognitive resources, reducing their ability to suppress irrelevant information. This results in greater effort being directed toward processing distractors, further elevating extraneous cognitive load. Measuring the effort students expend on irrelevant information or redundant actions—key indicators of extraneous cognitive load—could provide valuable insights for educators aiming to enhance instructional design. By accurately assessing perceptual and working memory loads, educators can reduce extraneous cognitive load and maximize germane load, paving the way for more effective instructional strategies. The following sections will explore potential methods for measuring these loads.

1.2 Individual differences and importance of measuring mental load

Research on digital learning technologies often attributes individual differences in learning outcomes to variations in mental load. However, direct measurement of the mental load experienced by learners is rarely conducted [17]. This gap is not due to a lack of interest but rather to significant practical and theoretical challenges that make obtaining reliable and valid mental load measurements difficult [10]. Understanding how individual differences influence performance on learning tasks is crucial, as these differences can substantially impact effects of load in working memory. Working memory capacity is strongly linked to an individual's ability to regulate attention. Its central executive function, which operates under voluntary control, varies across individuals [10].

Intrinsic cognitive load is influenced by both the inherent complexity of the learning material and the learner's familiarity or expertise in the subject matter. Therefore, identifying intrinsic load levels for each learner is critical for optimizing their learning experience [17]. However, obtaining accurate and reliable measures of mental load can be challenging, especially when learners are unfamiliar with the material. In such cases, learners may struggle to determine whether their difficulties arise from the complexity of the content or the instructional design, complicating efforts to distinguish between intrinsic and extraneous cognitive loads [18].

Furthermore, variations in mental load sources can result in similar overall mental load levels for different learners, making it difficult to identify the specific origin of the load. For this reason, measures of mental load should not be assumed to reflect an overall load but may instead be used to assess different types of load [10], [19].

1.3 Methods of assessing mental load. Eye-tracking

The available methods for assessing mental load can be categorized based on two key dimensions: objectivity (subjective versus objective) and causal relation (direct versus indirect) [17]. The objectivity dimension differentiates between subjective self-reported measures and objective observations, which include behavioral, physiological, or performance-based data. Subjective methods often rely on participant ratings to gauge the difficulty of learning materials as an indicator of mental load. Conversely, direct objective methods encompass techniques such as eye-tracking, dual-task approaches, and neuroimaging tools like functional near-infrared spectroscopy (fNIRS) [10]. While all these methods have been supported by evidence for their effectiveness in measuring mental workload, their validity is context-dependent [20], [21]. For this study, we selected eye-tracking as a means of assessing mental workload due to its ability to effectively capture variations in mental demand.

Research has shown that blink activity (latency and rate), pupil size, and fixation duration and rate are significantly associated with varying levels of working memory demand. These metrics, controlled by different parts of the nervous system, offer complementary insights into cognitive activity [10]. Certain aspects of eye activity serve as effective tools for distinguishing between various levels of mental load [22].

Among eye-tracking measures, pupil size has been extensively studied as an index of mental effort and processing load [16], [20], [21]. A large body of research suggests that pupil size fluctuates in response to mental load, as well as other factors such as drowsiness, emotional states, and mood [10], [23], [24]. Although pupil size is a reliable indicator of mental workload, it primarily reflects the intensity of the workload without specifying its origin or the stage at which it occurs.

While fixation-related eye movement parameters are considered valuable indicators of mental workload, research has yet to reach a consensus on their interpretation [25], [26]. Studies have reported contradictory findings, with fixation duration either increasing or decreasing as mental workload rises [16], [25], [26], [27], [28]. [16] suggest that these discrepancies stem from differences in the types of mental workload assessed in previous studies. Building on this, Liu et al. [16] proposed that fixation-related eye movement parameters can complement pupil size measurements to index general workload and distinguish between perceptual and working memory loads. According to load theory of selective attention [15], the combined effects of perceptual and working memory load on fixation patterns reveal how much relevant and irrelevant information is processed during a task. High perceptual load, indicated by shorter fixation durations and higher fixation frequencies, suggests limited processing of relevant information, requiring more fixations to comprehend materials, thus increasing extraneous cognitive load. Conversely, high working memory load, reflected by longer fixation durations and lower fixation frequencies, implies exhausted cognitive resources, leaving students unable to suppress irrelevant information, further increasing extraneous load.

Eye movement data can help identify sources of extraneous cognitive load and guide teachers in improving instructional effectiveness. For example, shorter fixation durations and higher fixation frequencies suggest that students are processing only small portions of relevant information at each fixation, which may indicate excessive perceptual load due to overly dense materials. In contrast, longer fixation durations and lower fixation frequencies suggest that students are struggling to process and organize the presented information, potentially indicating that they have difficulty identifying key content and allocating cognitive resources effectively [16]. In both cases, redesigning materials for better clarity and organization, as well as teaching efficient interaction strategies, can reduce unnecessary mental load and enhance learning outcomes.

1.4 Sex-related differences in mental load and learning performance

Among individual differences, sex-related variations in cognition have been observed in spatial and verbal tasks, with males often showing an advantage in spatial measures, while females excel in verbal measures [10]. Studies on working memory tasks also suggest sex-related differences in neural activity and brain activation patterns, indicating that males and females may adopt different strategies to complete similar tasks [10], [29], [30], [31], [32], [33], [34], [35].

Research by Chen et al. [36] examined the effects of gender and captions on learning performance and motivation using a digital map with GPS features to support contextualized English learning. The results showed that while gender similarities were apparent in contextualized learning, differences emerged under specific conditions.

For example, male learners performed better without captions, possibly due to the redundancy effect, which occurs when unnecessary information distracts from key content and overloads working memory [12], [36], [37]. Male learners may have been more easily distracted by captions, reducing their comprehension of the dialog, whereas female learners managed to maintain attention and motivation [36]. In contrast, female learners appeared better able to focus on the main material and demonstrated greater motivation, consistent with prior research showing that females excel in multimodal learning environments [38], [39], [40].

Similarly, our prior research identified sex-related differences in perceptual load, suggesting that males and females process visual information differently under varying levels of mental load [32], [33]. We hypothesize that these differences in perceptual load may explain the findings by Chen et al. [36], where males struggled with captions, resulting in lower motivation and comprehension.

These findings have important implications for the design of TEL. To create more effective and inclusive learning environments, it is essential to consider sex differences when developing multimedia or web-based educational resources [10], [36]. In this review, we specifically focus on sex-related differences as a key aspect of individual variations. The next section will present results from our previous studies [32], [33]. examining sex-related differences in numerosity perception and perceptual load. These results provide valuable insights into the cognitive mechanisms underlying these differences and underscore their implications for enhancing educational design.

2 REFERENCED RESULTS: BRIEF OVERVIEW

In our previous studies [32], [33], we explored sex differences in numerosity perception, visuospatial abilities, task performance, and their connections to working memory load and perceptual load. This research was motivated by the underrepresentation of females in STEM fields (science, technology, engineering and mathematics) and the potential role of cognitive factors, such as visuospatial abilities and perceptual processing, in explaining these disparities. Using eye-tracking technology, we revisited and expanded upon Krueger's foundational work [41], which identified sex-based differences in numerosity estimation—an area that has received limited attention in contemporary research. Numerosity perception refers to the ability to spontaneously estimate and mentally represent the size of a set, a skill closely linked to mathematical abilities and broader cognitive functions. It is supported by the Approximate Number System (ANS), a core cognitive mechanism responsible for processing non-symbolic numerical information. Existing research indicates that ANS acuity correlates with mathematical performance, making numerosity perception a critical area for studying individual differences in STEM-related learning and achievement.

Our research addressed two primary questions:

1. Do males and females differ in perceptual load during numerosity estimation tasks?
2. How are these differences reflected in cognitive performance and eye-tracking metrics?

2.1 Participants

Twenty-one participants (12 females), aged 20 to 50 years (mean age = 29.2), participated in the study. All had normal or corrected-to-normal vision. Participation was voluntary, with written consent obtained in line with the Declaration of Helsinki. Participants were unaware of the experimental conditions prior to the study.

2.2 Materials and procedure

The experiment utilized 3D moving objects to create realistic video simulations for object identification and numerosity estimation tasks. Targets, marked with colored boxes were presented within scenes featuring varying numbers of objects. The task was programmed with ExperimentBuilder and conducted using EyeLink Portable Duo, with eye movements recorded at 1000 Hz using a head-fixed mount for consistency.

The experiment included two blocks: an instructional block with examples and a test block comprising 22 trials of approximately one-minute videos. In the test block, 14 videos contained targets while 8 included only distractors. Task difficulty varied with the number of objects in each scene (1 to 17). Participants pressed predefined buttons to identify targets and later performed a numerosity estimation task based on the maximum number of candidate targets in a scene. This estimation task was designed to minimize bias and enhance accuracy, drawing on Krueger's method [41]. The entire session lasted about 25 minutes, providing comprehensive data on object identification, numerosity perception, and eye-tracking metrics.

In the dual task experiment, we combined multiple-object tracking with a numerosity estimation task. Participants' eye movements were recorded to capture metrics such as fixation duration and fixation rate, serving as indicators of perceptual and working memory load. Reaction time (RT) and accuracy were analyzed to assess task performance, offering a comprehensive understanding of the interplay between mental load and performance while highlighting sex-based differences in perceptual processing and task engagement.

The results showed similar accuracy rates between females (56.61%) and males (57.34%) and negligible overall differences in reaction times (females: 1950.03 ms; males: 1954.8 ms). However, task complexity revealed contrasting trends in reaction times: males exhibited a steady decline as task demands increased (from 2300 ms to 1540 ms), suggesting greater processing efficiency under higher complexity. In contrast, females demonstrated a gradual increase in reaction times (from 1950 ms to 2200 ms), indicating greater mental effort as task difficulty rose (Table 1).

Additionally, the study revealed notable sex-based differences in perceptual and working memory load during estimation tasks. Females exhibited shorter fixation durations and higher fixation rates compared to males, suggesting elevated perceptual load (Table 2). Specifically, the Mann-Whitney U test revealed that males had significantly higher average fixation durations (N = 198, Mdn = 360.42 ms, IQR = 86.64) than females (N = 264, Mdn = 324.72 ms, IQR = 75.70; U = 22874.00, p = .022). Conversely, females demonstrated a significantly higher fixation rate (N = 264, Mdn = 157.06 fixations per minute, IQR = 32.98) compared to males (N = 198, Mdn = 152.8, IQR = 33.65; U = 22959.50, p = .025).

These findings emphasize that sex differences in numerosity perception are driven more by variations in perceptual load than by inherent visuospatial abilities.

They also reinforce the importance of considering working memory load and perceptual load in the design of educational tools and strategies, particularly in STEM education.

Table 1. Reaction time and accuracy by sex

Metric	Females	Males
Accuracy Rate (%)	56.61	57.34
Reaction Time (ms) – Overall	1950.03	1954.8
Reaction Time (ms) – Low Complexity	1950	2300
Reaction Time (ms) – High Complexity	2200	1540

Table 2. Summary of fixation metrics by sex

Variable	Females (Mean ± SD)	Males (Mean ± SD)	Mann-Whitney U	P-Value
Average Fixation Duration (ms)	357.36 ± 73.42	377.69 ± 99.48	22874	0.022
Fixation Rate (per minute)	156.59 ± 25.26	151.88 ± 32.64	22959.5	0.025

Note: Table 2 adapted from: [32].

3 DISCUSSION

3.1 Implications for technology-enhanced learning

Eye-tracking technology has been proven to be valuable for identifying behavioral responses, assessing mental load, improving human-computer interaction (HCI), and informing interface design by adapting visual elements based on user data [42]. In the context of TEL platforms, real-time eye-tracking data offers insights into learners' mental and emotional states, enabling personalized and adaptive learning experiences through advanced user profiling [43].

This topic has gained considerable attention, with a few notable TEL systems incorporating eye-tracking technology to enable real-time content adaptation based on learners' needs. For example:

1. **AdeLE** [44]: A flexible, platform-independent system that seamlessly integrates with existing learning management systems (LMS). It enhances the learning process by offering tailored activities based on fine-grained user profiles, which link eye-tracking data with content tracking information.
2. **E5learning** [45]: This system uses real-time eye-tracking metrics, such as number of blinks and fixations, and pupil diameter, to evaluate cognitive workload, comprehension issues, and fatigue, dynamically adapting content to the learner's needs.
3. **ESA Interface** [46]: Designed to assess users' motivational states, this system provides affective and instructional feedback to foster engagement.

Despite extensive research, only a limited number of platforms and systems have fully embraced these advancements. Recent efforts include Protus (PRogramming TUtoring System), a TEL platform for teaching Java programming. Protus utilizes learning style identification and content recommendation to personalize courses. By analyzing learners' preferences, it adjusts content to align with individual needs, creating a highly interactive and customized educational experience [47]. In TEL systems like Protus, learning styles can be classified using the Felder-Solomon Index of Learning Styles (ILS) questionnaire [48] into the following categories: 1. Active or reflective learners; 2. Sensing or intuitive learners; 3. Visual or verbal learners; 4. Sequential or global learners. Authors of [2] proposed enhancing Protus by integrating eye-tracking data to assess learners' cognitive and emotional states in real time. This integration would enable dynamic content adaptation, improving engagement and outcomes. For example, learners focusing more on diagrams than textual explanations might benefit from content aligned with a visual learning style. Eye-tracking data could also identify usability issues or problematic material, prompting the system to adjust accordingly while enabling teachers to add supplementary explanations. Additionally, areas of interest (AOIs) identified through eye-tracking help ensure learners focus on the most critical screen elements [2].

Although comprehensive literature reviews address TEL's role in higher education [2], [49], limited evidence exists regarding its impact on perceptual load, particularly through eye-tracking metrics. Load theory of selective attention [15] can provide an appropriate framework for evaluating the sustainability of learner mental processes involved in technology-based learning and developing effective instructional approaches for enhancing instructional efficiency of such learning environments by optimizing their perceptual and working memory load conditions. Our findings indicate that perceptual load varies significantly among individuals and is influenced by factors such as sex. These differences are particularly pronounced in tasks like numerosity perception—a cognitive process closely tied to mathematical ability [33].

Despite advances in TEL, there is still no comprehensive model that integrates individual learner characteristics, such as prior knowledge, working memory capacity, and domain-specific abilities, to predict the intrinsic difficulty of educational materials for a given learner in a specific context [7]. Research guided by cognitive load theory has sought ways to manage high intrinsic cognitive load, such as by measuring and adjusting for learners' prior knowledge [50] or by optimizing germane load imposed by different instructional materials [10], [18]. However, an alternative approach emphasizes the importance of understanding the role of perceptual load in learning processes to optimize TEL systems. By integrating findings on perceptual load, based on eye-tracking metrics, TEL systems could be tailored more effectively to address individual learners' cognitive requirements, help identify sources of extraneous load and guide teachers in improving instructional effectiveness. This approach is particularly significant for the development of future systems designed to assess mental workload. These systems could directly address mental workload at its source. For example, synchronizing or physically integrating sources of related information might reduce extraneous load or perceptual load. Furthermore, employing well-designed visual cues to direct learners' attention to key elements of instructional materials could mitigate split attention and improve overall learning efficiency [3].

Our findings suggest that sex differences in numerosity perception are partially linked to differences in the ability to inhibit distracting information. Inhibition plays a critical role in suppressing irrelevant cognitive processes [51]. In visual search tasks, selective attention prioritizes the processing of relevant sensory information while filtering out distractors [52]. In our study, females demonstrated a stronger ability to inhibit distractors but reported lower and less accurate numerosity estimates than males. This discrepancy was associated with lower working memory load but higher perceptual load in females, as evidenced by shorter fixation durations and higher fixation rates. These observations align with findings by [36], where male learners struggled with comprehension due to being more easily distracted, whereas female learners were better at maintaining focus on the primary content.

It is also important to note that attentional skills, such as attention switching, can be developed through training. For instance, studies have shown that both children and adults who frequently play action video games experience greater interference from distractors under high perceptual load but also develop more efficient attentional processes [53], [54]. This suggests that video games may enhance the ability to manage perceptual load, opening avenues for future research. Training students in general skills like attention switching could potentially offer transferable benefits across various tasks and knowledge domains [10]. However, educators should remain mindful of persistent individual differences that may influence outcomes.

Building on prior research, our study proposes the use of metrics such as fixation duration and fixation rate to assess perceptual load. These measures provide actionable insights for designing adaptive TEL systems that cater to individual learners' needs, ultimately enhancing educational outcomes.

4 CONCLUSIONS

This study underscores the significant role of eye-tracking technology in advancing technology-enhanced learning (TEL) systems. By leveraging metrics such as fixation duration and fixation rate, TEL platforms can assess perceptual and working memory load, enabling adaptive learning environments tailored to individual needs. Our findings highlight sex-based differences in numerosity perception, driven by variations in perceptual load and the ability to inhibit distractors. These insights emphasize the need to account for individual differences in learning design, particularly in STEM education. Furthermore, training skills like attention switching could enhance learners' ability to manage mental demands, offering promising avenues for future research and development in TEL systems.

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