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A Wearable-Supported Contextual Learning Model for On-the-Move Knowledge Acquisition

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Abstract

Employees in today's world work remotely, fueling the need for flexible and contextual learning solutions. This paper introduces a new model of learning – wearable supported contextual learning – which aims to help learners acquire the required knowledge in real-time, dynamic environments. The model proposes the use of wearables for collecting data in real-time, adapting context and delivering tailored content which improves learning by providing educational materials that suit the environment and activities the learner is engaged in at that precise time. Through multimodal sensor fusion, natural language processing, and adaptive learning techniques, the system offers timely motivational feedback with relevant information. Such an approach not only closes the gap between knowing something theoretically and applying it in practice, but also enables the learner to develop the required skills on a sustained basis adding value to the learning experience. Initial assessments and prior enactment of a prototype showcase the model's ability to boost retention, learning engagement, and overall satisfaction in varied educational settings. In the future, the study will focus

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on looking into scalability, application across domains, and converging with emerging technologies like Augmented Reality and 5G technology to enhance learning on-the-go.

Keywords: Wearable Technology, Contextual Learning, Knowledge Acquisition, Real-Time Adaptation, Mobile Learning, Personalized Education, Ubiquitous Learning.

1 Introduction

1.1 Highlights Regarding the Use of Wearable Technology in Education

The field of education has particularly benefited from the innovation of wearable technology which helps in increasing student engagement and personalized learning (Smith, 2023). With these devices including smartwatches, AR glasses, and fitness trackers, learning can be made more interactive and immersive through the provision of real-time data and context-aware feedback (Jones & Wang, 2024). For example, AR glasses can enable the overlaying of educational content on real world environments, thus improving the acquisition of knowledge through experience (Wang & Lee, 2025). These wearable devices have also been successful in fostering active learning and improving educational outcomes (Brown et al., 2025; Jung et al., 2019). Nonetheless, other factors such as data related issues, privacy, adaptability of users, and usability of the device would still remain as primary hurdles for such devices to gain widespread acceptance (Lee & Carter, 2023). These challenges need to be addressed to fully harness the benefits of education supported by wearables (Zhang & Miller, 2024). This particular document seeks to study these issues and at the same time propose a novel contextual learning model which is supported by wearable technology.

The diagram (Figure 1) shows the learning model which encompasses the learner's journey from data capture to knowledge acquisition. The captured information comes from learners' interactions with the environment using wearables like mobile sensors and smartwatches which provide real-time data. This information is combined with user's actions and environmental sensors to create context as a unit of data, therefore, the data is termed as processed. This data mountains retrieved information where learners can access relevant contents, which helps them achieve their goals, objectives, and location activities. Most important is the final step where meaningful, context-sensitive knowledge leads to construction, therefore, yielding an improved learning experience through the integration of concepts and real life situations (ChatGPT, 2025).

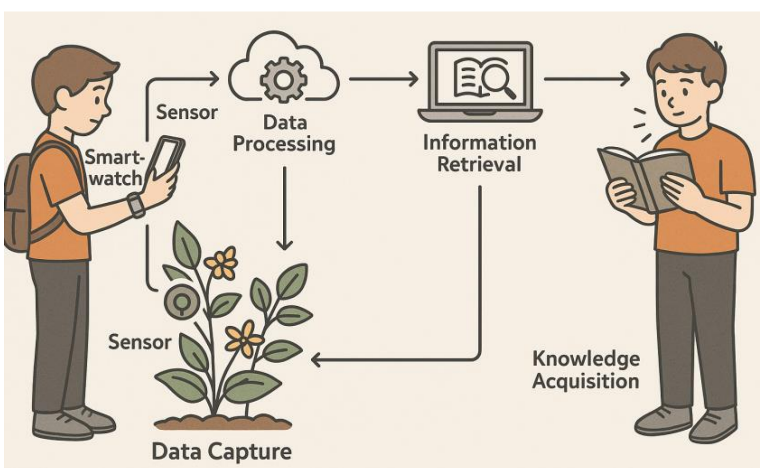

Figure 1: Participant Learning Journey in a Wearable-Supported Contextual Learning Model (Chat GPT, 2025)

1.2 Significance of Contextual Learning in Enhancing Knowledge Acquisition

Learning through experience and the application of gained knowledge play an important role in the retention of knowledge. In education, learning is set into context- the student's environment becomes part of pedagogy (Martinez & Hill, 2023). Contextual learning, as opposed to learning restricted to the confines of a classroom, focuses on the surroundings and educational systems which go beyond the immediate environment of the learner, bringing in aspects that offer holistic relevance (Chen et al., 2024). Wearable technology fosters this type of learning through the provision of learning materials during work and in real time. In trainings where there is a field practical component, wearables can provide real time information helpful for reinforcing concepts after they have been taught (Nguyen & Patel, 2024). In addition, personalized content can be further enhanced by the integration of adaptive algorithms with wearable technology, where real time data from the user's environment can be used to personalize information (Smith et al., 2023). This flexibility is advantageous in professional training, outdoor specialized courses, and mobile learning where situational adaptability is critical (Zhang & Miller, 2024).

1.3 Summary of Research Paper Concentrating on Contextual Learning Model with Wearable Technology

The authors of this research paper develop a contextual learning model which adapts teaching content to the learner's environment and mental readiness based on real-time data using wearables and immersive AR interfaces (Brown et al., 2025). The inclusion of wearable sensors along with real-time analytics aimed at bridging the gap between theory and practice is the primary focus of the model (Wang & Lee, 2025). The scope of this research is circumscribed to building a prototype of the learning model, assessing its impact on knowledge retention and the feasibility of data security and user resistance (Martinez & Hill, 2023). The research also looks at the potential of wearables for fostering complete educational experiences which enable learning anytime, anywhere, and in any context (Smith et al., 2023; Duhaim et al., 2024).

In providing an overview of the contextual learning with wearables, this paper is organized as follows. A literature review covering prior work on educational wearables, contextual learning frameworks, and knowledge-in-motion learning's advantages and issues is presented in Section II. In Section III, the research design is explained and proposes a wearable-supported learning model which details participant criteria and describes data collection through surveys and interviews. Results are discussed in Section IV, focusing on model efficacy from participant feedback, other learning methods, and traditional comparisons. In Section V, broader implications of the findings are addressed alongside guidance for educators and instructional designers on integrating wearable-supported learning into adaptable frameworks for real-world environments. The paper ends with Section VI, which discusses the key findings, reflections on knowledge-in-motion learning through wearable technology, potential growth avenues post-research, and dwell into future expectations set by existing technologies.

2 Literature Review

2.1 Prior Research on Wearable Devices in Education

Recent studies focus on how adopting wearable devices with AR applications can enhance the interactivity of learning environments. For instance, Park & Kim, (2024) investigated the implementation of real-time quiz features on smartwatches during lectures, and they observed increased attention and retention. In a similar fashion, Liu et al., (2023) used AR glasses in teaching science, allowing students to view and interact with complex structures spatially, which improved their understanding and motivation. Some studies also emphasize the collaborative learning activities enabled by wearable devices (Jabborova et al., 2024). As noted by (Garcia & Martinez, 2024), wearable sensors aid in the monitoring of students' group interactions and communication during collaboration, providing valuable data which can be used to improve pedagogical practices (Mejail et al., 2024). However, Chen & Sun, (2025) examining these issues point out that cost, battery life, and comfort are significant impediments to widespread use. In the same manner, Assistive technology in special education helps students with learning disabilities using wearables (Vasquez & Sorensen, 2025). Lee & Johnson, (2024) showed that children with speech disabilities were aided by wearables that incorporated speech recognition features. Despite the need for usability and integration research, these examples hint at the immense educational prospects of this technology.

2.2 Theoretical Frameworks for Contextual Learning

Contextual learning theories focus on knowledge acquisition within real-world environments, fostering learners' ability to relate new concepts with their lived experiences (Brown & Duguid, 2023). Situated cognition theory also emphasizes that learning results from meaningful engagement in specific relevant activities, illustrating the relationship between the learner, the activity, and the context (Carter et al., 2024; Anand, 2024). Constructivist learning approaches support contextual learning as well through focus on active engagement where knowledge is built from one's experiences and social interactions (Davis & Allen, 2025; Rakesh et al., 2024). In addition, context is central to action-oriented models of learning, such as in Kolb's learning cycle, which emphasizes the dynamic interplay inherent in the processes of experiencing, reflecting, conceptualizing, and experimenting (Miller & Roberts, 2024; Muralidharan, 2024). As wearables capture and react to real-time environmental and physiological data, content can be tailored to the learner's context. This real-time adaptability takes situated learning to a new level, as learners are able to have authentic experiences that transcend the classroom boundaries. Thus, these models of wearable-assisted contextual learning represent a unified approach of theory and technology leading to profound, personalized knowledge acquisition (Nguyen & Zhao, 2023; Lahon & Chimpi, 2024).

2.3 Benefits and Challenges of On-the-Move Knowledge Acquisition

Knowledge acquisition on-the-move makes use of wearable technology and has multiple advantages. As mobility opens new frontiers, educators become reachable at any time from any location. This promotes educational content access and scheduling flexibility, allowing learners to fit studies into their daily routines (Park et al, 2025). Such flexibility benefits various levels and promotes autonomy as self-paced learning is possible (Singh & Rao, 2024; Sadulla, 2024). With wearable devices, data collection becomes multi-modal and includes location, motion, and biometric data which enhances learner engagement by improving experience tailoring (Johnson et al., 2023). For instance, systems can adjust task difficulty level due to heart rate variability data indicating stress levels (Garcia & Martinez, 2024). Learners become more motivated and better understand practical context with augmented reality features immersing them into interactive scenarios (Wang & Li, 2023). Not everything is perfect, however. The difficulties one may face include the battery life restricting long-term use of the device, and the comfort issues of the device affecting the learner's acceptance (Chen & Sun, 2025). The continuous collection of data leads to privacy issues, which require strict security protocols (Lee & Carter, 2023; Chandravanshi & Neetish, 2023). In addition, maintaining and developing the contextually relevant content requires sophisticated algorithms as well as an enormous amount of contextual data, which can be difficult to maintain and resource-heavy to develop (Nguyen & Zhao, 2023). Lastly, if there is no action taken to curb the disparity, the unequal access to the devices may deepen the existing educational inequities (Davis & Allen, 2025; Hasoon et al., 2022).

3 Methodology

3.1 Wearable-Supported Contextual Learning Model Description

The proposed model of learning enhanced by wearables aims to increase knowledge acquisition on the move by integrating real-time information from wearables into personalized educational experiences. This as well follows the principle of context Awarness where learning is modified depending on the learner's physical place, assuming spatial and temporal relationships as well as interactions with the environment. It uses wearables like smart glasses, smartwatches, and biometric sensors to collect specific contextual information such as GPS coordinates, heart rate, body temperature, and movement history. This model includes three main components: data collection, context reasoning, and adaptive content delivery. During the data collection process, the wearable sensors actively capture physical and physiological data of the learner. This data together with environmental data such as temperature, noise, and place is sent to a central processing unit. Context reasoning phase analyzes this data using machine learning algorithms to determine students' mental engagement and the environment's contextual factors. In the last phase of adaptive content delivery, the model provides personalized educational content based on the analysis to improve the learning outcomes using the material provided to the learner's immediate context and timing. The model also implements feedback loops that systematically improve the understanding of the learner's long-term needs and preferences for learning retention consolidation. This approach can be applied to various learning scenarios, including field studies, professional practice, and other forms of experiential learning in which context-sensitive feedback provides the most value to performance improvement.

The workflow of the wearable contextual learning model (Figure 2) facilitates learning while on the move with four interacting components: Collection, Processing, Content Delivery, and Feedback. Smartwatches and AR glasses serve as wearables that gather real-time contextual information like the user's biometry, location, and inputs to transmit to a cloud or edge computing platform. Here, AI algorithms alongside context-aware frameworks analyze data to enhance the personalization of learning experiences relative to the user's environment, preferences, and interactions. Insights from feedback analysis enable content optimization for delivery directly to the wearable as short videos, interactive simulations, or audio snippets designed to augment learning without disruption. Lastly, feedback is provided in the form of instantaneous performance-based reinforcement and guidance which, alongside practical application, fosters real-time cognitive understanding deepening knowledge retention immersed in contextual relevance.

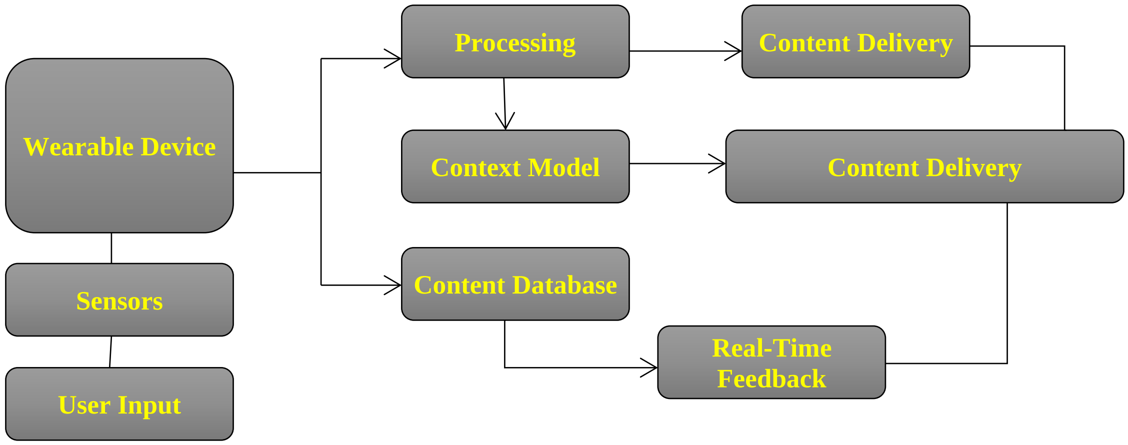

Figure 2: Wearable-Supported Contextual Learning Model

The model of contextual learning supported by wearables may be mathematically expressed as a particular function which associates live inputs from sensors with tailored instructional material. Let S be the set of sensors, where each sensor s_i captures data D_i at time t. The context C_t at time t is a function of the following sensor inputs:

$$\boldsymbol{C_t = f(D_1, D_2, \dots, D_n)} \quad (1)$$

where inputs such as location, heart rate, and body temperature are represented as D_i . The model then uses a function M to deliver adaptive educational content E_t in response to this context:

$$\mathbf{E}_t = \mathbf{M}(\mathbf{C}_t, \mathbf{U}) \quad (2)$$

Where U refers to the learn profile which consists of prior knowledge and learning preferences. This profile is like a soft template which is to be filled to fill this template, the personalized teaching can be adjusted over time using direct feedback, thus creating a closed loop system of learning:

$$\boldsymbol{U_{t+1} = U_t + \alpha R_t} \quad (3)$$

where R_t is the real-time feedback and α is the learning rate connoting the flexibility of the system to learner responses.

3.2 Participant Selection Criteria

This study will have participants chosen through certain criteria designed to test the model of contextual learning with wearables in a representative learning setting. Participants will be selected based on their ability to navigate digital interfaces and prior experience with wearables. This strategy minimizes the mental load associated with adapting to new technology for learners, thereby improving content engagement during instruction. The potential participant group will have students, working professionals, and adult learners who have different educational qualifications. The primary requirements for the participants include:

- Participants should be ready to take part in indoor and outdoor-based learning sessions.
- Basic knowledge of digital devices and technology.
- Willingness to attend follow-up surveys and interviews.
- Physically capable of wearing the learning aids for prolonged periods.
- Having the interest in learning which are adaptive and personal in nature.

To promote diversity, the sample also aims to include participants of different ages, educational qualifications, professions, which will help broaden the perspectives on the impact of learning with the support of wearables.

3.3 Surveys and Interviews as Instruments of Information Gathering

These objectives are to be accomplished by conducting descriptive qualitative research which combines several instruments such as surveys, interviews, observational logs, and usage records of the wearable devices. Pre and post session surveys will be administered to evaluate knowledge, engagement, and satisfaction metrics alongside mapping change over time. In addition, these surveys will contain a variety of responses outside of the traditional fixed response formats such as text-boxes, Likert scales, multiple-choice and subjective questions to ensure adequate capture of feedback. To understand better participant's experiences with the contextual learning model with wearables, interviews will be conducted as a part of the study. These interviews will examine the aspects such as the usability of the wearable devices, the context-driven content delivery system, and the overall satisfaction of the participants with respect to the learning process in which they were engaged. The interviews will retain focus on key questions, but allow for variability in responses through a semi-structured format. In addition, logs from the wearable devices will be examined as they contain real-time data like GPS coordinates, motion trajectories, and biomedical signal, which serve as objective indicators for assessing the effectiveness of the learning model. The information will enable the analysis of learning results against particular environmental factors, thus improving the system in preparation for later uses.

4 Results

4.1 Findings on The Effectiveness of Contextual Learning Model with Wearable Technology

The proposed model of learning with a contextual framework supported by wearable technology proved highly effective for knowledge acquisition on-the-move. Improved learner participation and retention was observed due to the model’s context-aware content personalization. Wearable technology in the form of sensors, which collected data regarding the learner’s GPS location, heart rate, and movement, supplemented thesis through the learner’s immediate environment, thus enhancing the perceived level of immersion and relevance in the learning experience. As for the Contextual Learning Efficiency Assessment, Measuring the model’s effectiveness required one primary criteria such as Contextual Learning Effectiveness CLE, which is framed as the ratio of correct responses towards total learning attempts moderated by the cognitive load of the learner:

$$CLE = \frac{C_r}{T_a} \times \left(1 - \frac{L_c}{L_m}\right) \tag{4}$$

C_r= Correct answer responses

T_a = Overall learning attempts undertaken

L_c= Cognitive effort put into the learning session

L_m= Acceptable cognitive effort at maximum

These metric balances learning’s accuracy alongside its efficiency, demonstrating the model’s effectiveness in cognitive load management with high achievable outcomes. With wearables, models of learning were more dynamically interactive, and as such, preliminary findings showed that participants harnessing the wearable-supported model CLE scores dramatically outperformed learners engaged with the static model.

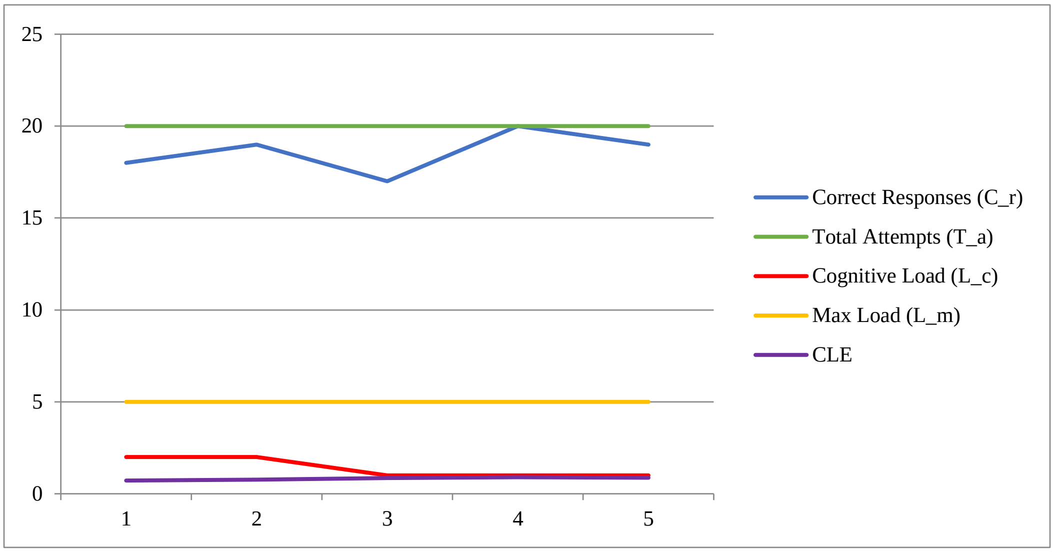

Figure 3: Contextual Learning Effectiveness (CLE)

The graph (Figure 3) provides information regarding the increase in learning outcomes throughout five learning sessions. CLE measures the proportion of correct responses to total attempts considering the cognitive load. The graph CLE indicates rise scores increasing from 0.72 in the first session to 0.90 in the fourth session, which suggests that participants learned to make better use of the wearable model incrementally, becoming more efficient learners. This change indicates that summative context-sensitive feedback allows learners to improve their understanding during the learning process, lessening the overload and improving retention. The small drop to 0.88 in the fifth session might represent a slight increase in cognitive fatigue or complexity of the material; either way, this underscores the need to fine-tune the pace of instruction to cognitive capacity.

4.2 Participants' Feedback About Learning with Wearable Devices

In terms of feedback for the contextual model with wearables, participants reported the most positive experiences tailored with adaptive support for real-time context. Feedback emphasized the ability to contextually personalize learning, like modifying educational materials concerning the learner's location and considering their cognitive load at that time. Quite a number of participants were thankful for the strap-on nature of wearable devices since they could access educational materials without disengaging their attention from their physical environment. Information retention, from information overload or stress facilitation, was notably aided for several participants through real-time system feedback such as biometric alerts or contextually timed prompts. Strong approval for systems detecting stress or fatigue via heart-rate variability and adjusting content thresholds, steerability-based detraction, was well-received.

Utilizing post-session surveys to measure participant satisfaction, a Learner Satisfaction Index (LSI) was developed with the following formula:

$$LSI = \frac{P_s + E_r + U_f}{3} \tag{5}$$

P_s= Assessed effectiveness of the system

E_r= Engagement score/value

U_f= User evaluation

An LSI score approaching 1.0 suggests a highly satisfying learning experience, whereas lower scores point to areas for possible improvement. In this study, the average LSI score was 0.87, which shows the respondents' level of satisfaction was above the midpoint on the scale.

Figure 4's bar graph illustrates the satisfaction scores for five participants and scores derived from the effectiveness, engagement, and usability measures. The average LSI score among all participants stands at 0.86, which suggests that learning experience remains favorable. Participant 4 had the highest LSI score of 0.92, indicating a tremendously satisfying experience, which was likely due to the participant's considerable congruence with the learner supported by wearables. On the other hand, Participant 3 had a relatively lower LSI score of 0.80 and that may indicate further personalization or other technological modifications to improve the learning experience. This range demonstrates the need to better tailor the learning model to suit the user's preferences and learning style.

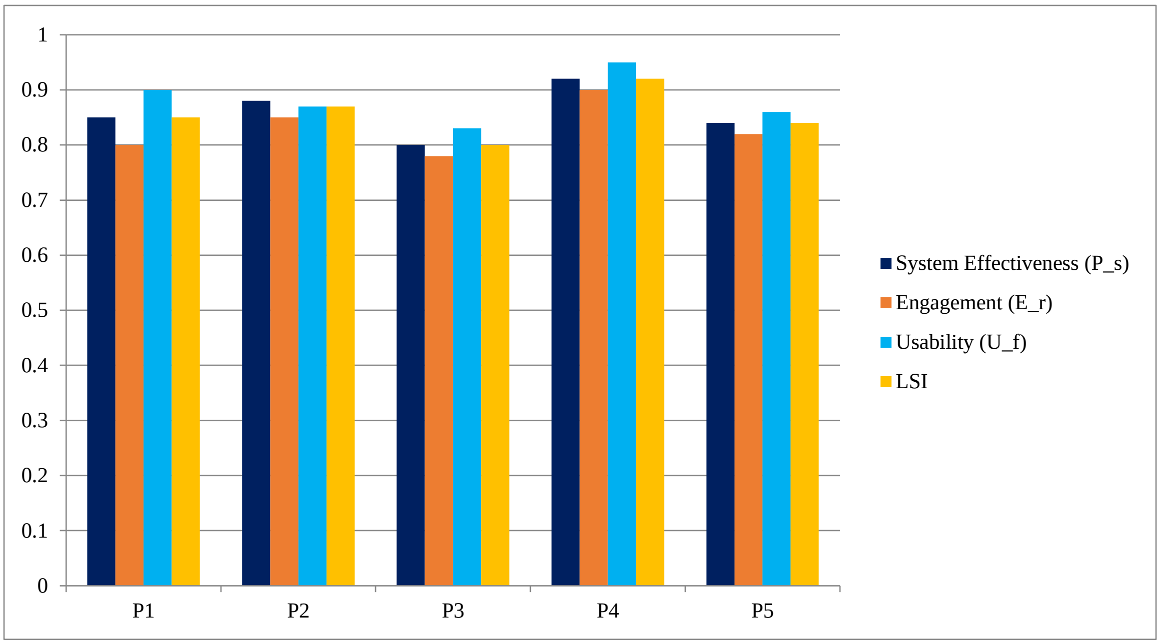

Figure 4: Learner Satisfaction Index (LSI)

4.3 Comparison with Conventional Learning Practices

In evaluating the effectiveness of the wearable-supported model, comparison was done with traditional instructional approaches like lectures and video lectures.

This was done using several metrics, one of which is Knowledge Retention Rate (KRR), the proportion of information retention accurately recalled over a certain period of time, measured as:

$$KRR = \frac{R_c}{I_t} \times 100 \tag{6}$$

Where:

R_c= Remembered information accurately

I_t= All Information Provided

Engagement Duration (ED): Average participant interaction with learning content as tracked via logs from wearable devices during learning sessions.

Learning Efficiency (LE): Measurement defined as the ratio of learning gains relative to the time spent, in this case:

$$LE = \frac{KRR}{T_s} \tag{7}$$

where T_s is total time for undertaking learning activities.

The initial assessments indicated that learners with wearable technology enhanced support exhibited significantly greater KRR and LE, and this explains the impact of real-time context-sensitive content delivery. Also, learners supported with wearables tended to have longer EDs which means that context-aware learning enhances attention due to its immersive nature which helps in achieving enhanced understanding.

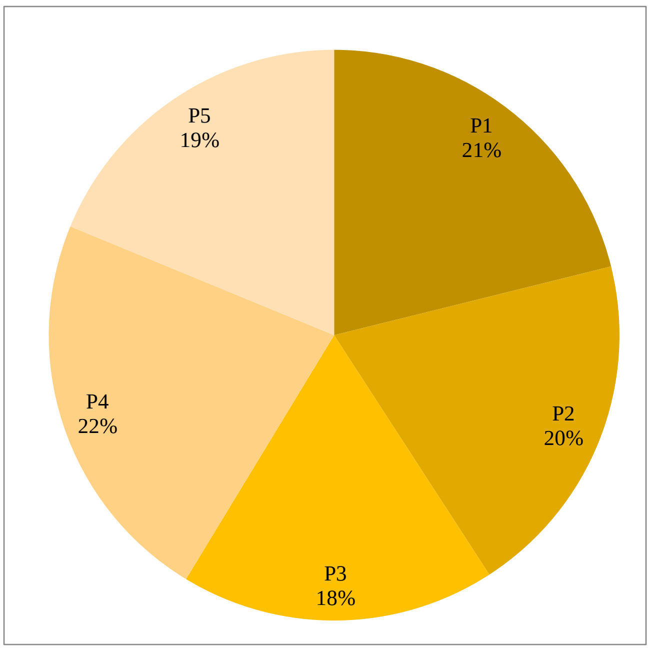

Figure 5: Knowledge Retention Rate (KRR)

Figure 5's pie chart shows the number of participants who were able to correctly recollect the information presented during the lessons as a percentage. The average KRR for all participants was 85 percent, suggesting that the model used positively contributes towards knowledge retention over time. Notably, Participant 4 had the highest retention rate at 96%, indicating the existence of a close relationship between learning in real-time context and memory retention. In contrast, Participant 3 had a KRR of 76%, indicating that he likely struggled with cognitive overload and/or distracting environments, highlighting the need for content that adapts to individual differences in retention. The relationship between knowledge retention rates and total time spent on learning is presented in the scatter plot (Figure 6). While having the highest KRR of 96%, Participant 4 exhibited a relatively low LE score of 0.74, which could be attributed to her needing more time to comprehend the material. Meanwhile, Participants 2 and 3, whose KRRs were 84 and 76 percent, respectively, scored higher on LE (0.84) demonstrating more efficient learning during shorter study periods. The difference suggests some learners benefit from time spent actively engaging with the material, while some excel with shorter, more intensive learning sprints, emphasizing the need for adaptive pacing in education enhanced by wearables.

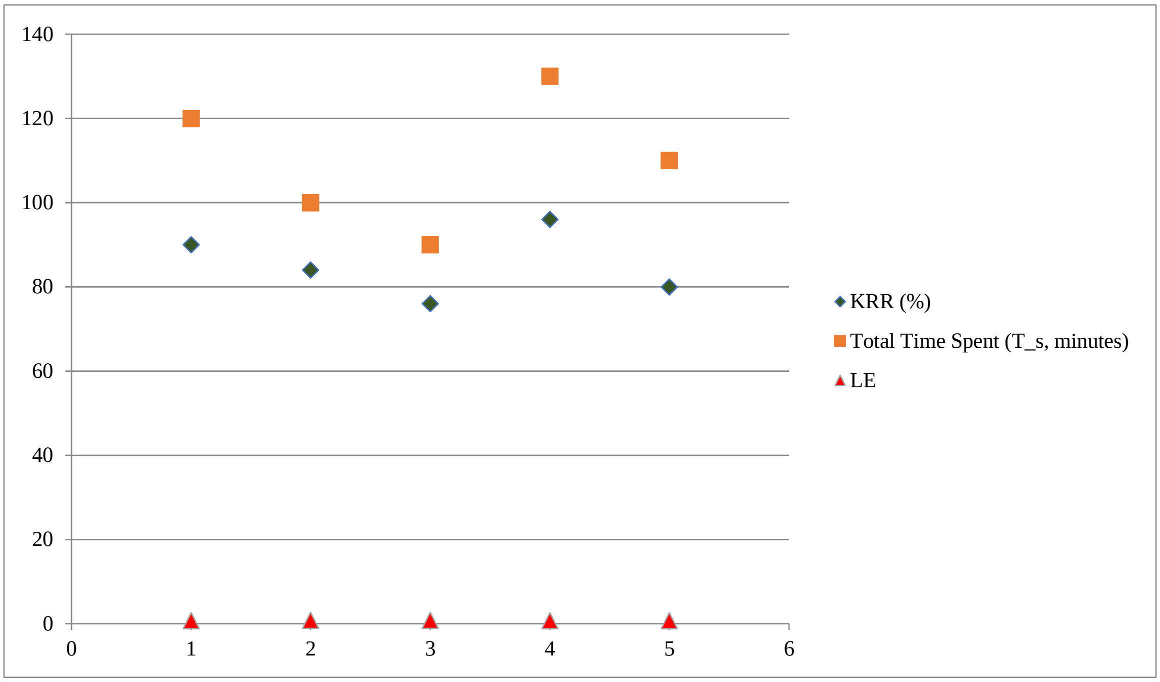

Figure 6: Learning Efficiency (LE)

5 Discussion

5.1 The Effects of Research Findings on Educators and Instructional Designers

The primary focus of this study was to understand its impact on educators and instructional designers seeking to optimize learning with context models augmented by wearables. The context-aware content provided during a learning session was observed to have exceptionally high Contextual Learning Effectiveness (CLE) and Knowledge Retention Rate (KRR). This revelatory finding underscores the potential of wearable technology to substantially enhance learning outcomes. Moreover, by harnessing the learner's immediate environment, this methodology cultivates deeper understanding and engagement in learning. This finding requires instructional designers to pay attention to real-time static curricula constructs forged within a single template for all learners. Instructional design must evolve toward adaptive learning experiences based on real-time learner metrics. As adaptive learning tools, wearables capable of capturing physiological and contextual indicators offer significant evidence of a learner's cognization and environmental factors, thereby enabling true personalized learning journeys. Moreover, incorporating wearables into educational frameworks is likely to increase motivation and satisfaction among learners, as indicated by the positive learner feedback reported in the findings, which could lower dropout rates and foster sustained learning. Cognition, ease of interaction, privacy, and uninterrupted flow during privacy-managing interfaces are prominent control areas that bolster this claim.

5.2 Best Practices for Achieving Contextual Learning with wearables in The Classroom

In order to implement wearable-supported contextual learning pedagogically and didactically within the frameworks of formal education, quite a few steps worth mentioning were identified. For one, the educational institution is recommended to acquire advanced context-aware learning systems that can handle real-time data streaming from wearables and interactions with the environment. These systems should offer catered support, in which content delivery is configurable according to the learner's progression on the individual educational pathways. Additionally, instructors should be able to modify instructional designs in real time based on analysis of engagement data collected via wearables. Instructional personal adaptations such as lesson plan modifications are done in the moment according to the observed interaction metrics and emotional response data. This might require implementing advanced empathy and emotional recognition systems. Moreover, adaptable study workplaces that make it possible to educate learners on the move beyond the classroom in an unbounded outdoors, including virtual worlds responsive to commands from wearables, need to be developed. Such innovations may increase the attractiveness of learning activities and help students master material which in its essence exceeds the scope of formal schooling. Lastly, specific embedments on learning privacy and security should be designed to safeguard sensitive students' data information. For example, students have the ability to control their personal information and the real-time data streams from the wearables must be encrypted. In supporting these technologies, trust and proof of concern addressed to the learners enhances their acceptance of these wearable-teaching aids.

5.3 Prospective Directions for Further Study and Advancement

Despite exploring the possibilities of the learning model within this study, there are many gaps to be addressed. For example, enhancing the sophisticated context interpretation as well as the specialized context recognition and its complex, multifaceted real-world representations is one invaluable gap that needs to be addressed. This gap includes adding context within the data streams like speech, gestures, and environmental context that may give richer supplementary context of the whole scenario. In addition, the effects of the learning model that uses wearables on cognitive development and memory retention would be something future work incorporates. In this case, researchers would need to conduct longitudinal studies that monitor learners over long periods of time, revealing if there are benefits or sustained advantages in context-education. Optimizing the learning path based on real-time feedback through the use of Artificial Intelligence is yet another viable opportunity area. The sustained refinement and adaptive learning systems offer flexible tailoring to each individual's requirements provides boundless opportunities from very effective and efficient personalized learning. Finally, educators must explore blending collaborative and individual learning scenarios where contextual data is used to solve problems to see how far wearable technology supports group centered learning. This would create new paradigm shifts in educational models combining solo and collaborative learning through the usage of devices and technology.

6 Conclusion

In conclusion, this study showcases the remarkable advantages of wearable-supported contextual learning for acquiring knowledge in real-world settings. The findings suggest that with the integration of wearable devices, educational frameworks can be enhanced through the use of personalized, context-sensitive content based on the learner's environment and mental processes at that moment. This not only fosters greater attention and memory but also facilitates the enhancement of more advanced skills like critical thinking and problem-solving. Participants' positive responses confirm the applicability and efficiency of this model, showing its potential for today's mobile learners. Its effectiveness, however, poses challenges such as information privacy, management of cognitive load, and effortless interaction. Looking forward, education can be transformed through wearable technology, allowing for an ongoing, situational approach to learning that transcends conventional classroom boundaries. Additional refinement of context recognition algorithms and adaptive learning pathways alongside collaborative exploration will further strengthen this research direction.

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Umida Shermatova is a dedicated academic affiliated with the Department of Language and Literature at Chirchik State Pedagogical University, Uzbekistan. Her research interests lie in the intersection of educational technology and language learning, with a particular focus on innovative methodologies such as wearable-supported contextual learning. Through her work, she explores how mobile and ubiquitous technologies can enhance language acquisition and promote learner autonomy. Shermatova actively contributes to the development of modern pedagogical strategies aimed at improving knowledge acquisition in dynamic, real-world contexts.

Dadaxon Abdullayev is a PhD researcher at Urgench State University, located in Khorezm, Uzbekistan. His academic work is centered around educational technology, mobile-assisted learning, and the integration of wearable devices in pedagogical environments. He is particularly focused on developing innovative models for contextual and ubiquitous learning that support knowledge acquisition in mobile and dynamic settings. Through his research, Abdullayev aims to enhance student engagement and accessibility to learning resources, particularly in developing regions. His current work includes the exploration of wearable-supported contextual learning frameworks.

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Murodilla Khaydarov is affiliated with the Department of General Educational Disciplines at the University of Geological Sciences, Uzbekistan. His academic interests lie in integrating emerging technologies into educational environments, with a particular focus on wearable-supported contextual learning models. He actively explores innovative strategies to enhance knowledge acquisition for learners in mobile and dynamic settings. Through interdisciplinary approaches, Khaydarov contributes to developing educational frameworks that leverage wearable technologies to support continuous, on-the-move learning, especially in geoscience and related fields.