InerSens: A Block-based Programming Platform for Learning Sensor Data Analytics in Construction Engineering Programs

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ABSTRACT

Construction firms face challenges in sourcing qualified candidates for enhancing project outcomes through sensor data analytics. There are limited tools for teaching students from construction-related disciplines how to analyze sensor data. By harnessing the potential of block-based programming, this study designed a pedagogical tool, InerSens, to support construction engineering students with no prior programming experience to analyze sensor data and address real-world construction challenges, such as ergonomic risks. Twenty students participated in an experiment comparing InerSens and a traditional platform, Excel, for data analytics. Evaluations involved usability, perceived workload, visual attention, verbal feedback using the System Usability Scale, NASA TLX, eye-tracking metrics, and interviews respectively. InerSens was rated as 8.89% more user-friendly than the traditional tool, with a significantly reduced perceived cognitive load by 46.11%, and a more balanced distribution of visual attention during data analytics tasks. Through the evaluation of cognitive and usability factors, this paper extends the applications of Learning for Use and Cognitive Load theories, emphasizing their applicability in instructional design, revealing learner needs, and the potential to advance the development of pedagogical tools for data analytics.

Keywords: Sensor Data Analytics, Sensing Technologies, End-User Programming, Usability Engineering, Eye-tracking, Ergonomic, Risk Assessment, Construction Education.

INTRODUCTION

Advancements in sensing technologies in the construction industry have opened avenues for enhancing project performance. This is placing a demand on the workforce to meet the rising need for skills needed to deal with sensor data. The construction industry constantly presents a complex and dynamic environment, rich in information demands. In this domain, traditional and manual data acquisition approaches fall short when attempting to meet the demands of advanced construction management (Shen and Lu 2012). As a response to this, the construction industry is increasingly embracing sensing technologies to enhance performance (Mansouri et al. 2020). However, a noticeable disparity arises between the academic curriculum and the actual requirements of the industry, resulting in an inadequately prepared workforce (Ogunseiju et al. 2021). An instance of this could be presented with an evident construction challenge concerning work-related musculoskeletal disorders (WMSDs), causing substantial impacts on productivity and incurring expenses (Yan et al. 2017). To tackle this problem, researchers have extensively studied the utilization of affordable sensing technologies, such as Inertial Measurement Units (IMUs), to analyze and minimize WMSD-related risks (Bangaru et al. 2021; Yan et al. 2017). However, the abundance of data collected by these sensors necessitates a profound understanding of analytics for extracting valuable insights from the vast datasets (Krishnamurthi et al. 2020). Effectively managing the intricacies of sensor data analytics requires a comprehensive understanding of various aspects, including methods for data collection, data preprocessing, feature extraction, statistical analysis, and data visualization (Ngo et al. 2020). Therefore, analytics skills are necessary to extract meaningful insights from sensor-generated data, but construction firms struggle to find qualified candidates with these abilities, which limits their capacity to fully leverage sensor data analytics for enhanced project outcomes (Cheng et al. 2013; Mansouri et al. 2020). To bridge the gap between academia and industry demands, it is critical to provide construction students with the affordance to actively engage with these sensor data analytics techniques and use them in real-world circumstances.

Addressing the imminent data analytics skills shortage requires a viable pedagogical tool that effectively engages the future workforce in data analytics, utilizing user-friendly, efficient, and manageable technologies. End User Programming (EUP) or End User Development (EUD) shows effectiveness in acquiring data literacy, especially when supported by block-based programming environments (BBPEs). Researchers and educators from diverse fields concur that BBPEs have demonstrated great value in enhancing learners' domain-specific skills and fostering computational thinking (CT) in academic and professional settings alike (Glas et al. 2023; Rahaman et al. 2020; Skorik

2022). Within the domain of EUP, the technique of block-based programming simplifies coding by utilizing visual blocks (Coronado et al. 2021). With the use of a drag-and-drop interface provided by block-based programming, non-programmers may quickly and simply design and alter data analysis processes (Bau et al. 2017). To ensure efficacy and adoption, BBPEs must be customized for various user populations, making content and usability assessments significantly vital for effective instructional objectives (Glas et al. 2022; Rijo-García et al. 2022). Formative evaluation holds significant importance in identifying and addressing usability issues within Human-Computer Interaction (HCI) platforms (van Velsen et al. 2011).

Therefore, this research aims to investigate the design and usability evaluation of InerSens, a BBPE, for equipping students from construction-related disciplines to perform analysis on sensor data. The efficacy of the proposed pedagogy is evaluated from the context of ergonomic risk assessment. Formative evaluation is conducted by comparing the performance of InerSens with a traditional method, using Microsoft Excel, for analyzing sensor data ergonomic risk assessment. The evaluation includes assessing overall usability, perceived workload, visual attention, and verbal feedback obtained from users' experiences with InerSens and the traditional approach. Through this comprehensive evaluation, the research gained insights into the user experience and effectiveness of the BBPE in the context of construction sensor data analytics. Results of the evaluation of InerSens advance the underpinning theories: Learning for Use and Cognitive Load theory. The paper follows a structured format, starting with background information on relevant concepts in Section 2. Section 3 outlines the methodology, covering environment development, experimental procedures, and data analysis. Section 4 presents the experiment's results, and the conclusion synthesizes the findings, addresses study limitations, and discusses the practical implications of implementing the pedagogical tool in real-world learning environments.

BACKGROUND

Construction Sensor Data Analytics

The field of sensor data analytics encompasses the utilization of diverse sensor collection technologies, processing techniques, analysis methodologies, and interpretation approaches to shape and inform the decision-making perspective of users (Tsai et al. 2015). Mansouri et al. (2020) presented a more precise definition of sensor data analytics in the context of construction, referring to it as the process of analyzing raw data collected from construction projects. The objective is to extract useful insights and use them to make informed decisions in a variety of areas, such as project planning, execution, management, and control. Hence, construction-based sensor data analytics comprises the processing, evaluation, and presentation of data collected via sensing technologies to obtain useful information in forms that support informed decision-making (Akanmu et al. 2022; Louis and Dunston 2018). The adoption of advanced sensing technology in the construction sector is transforming how projects are executed, with an essential emphasis on safety and productivity. Laser scanners, GPS, RFID, IMUs, drones, and cameras are rapidly becoming indispensable tools for improving safety protocols and facilitating thorough project planning and execution (Akhavian and Behzadan 2015; Alizadehsalehi and Yitmen 2021; Majrouhi Sardroud 2012; Teizer and Cheng 2015). The advantages are inherent in the use of sensor data analytics methods, which enable experts to unearth crucial insights into operational patterns and trends. This leads to improvements in a variety of areas, including increased productivity, decreased costs, and the adoption of strong safety measures (Abioye et al. 2021). For example, wearable sensing technology such as IMU, is useful for collecting motion data from construction workers, aiding in occupational health analysis. Data from IMUs contribute to providing comprehensive information on the amount of physical stress and strains experienced by a worker while executing a construction task. Insights from analytics can help practitioners improve construction safety and productivity by early detection of musculoskeletal disorder risk factors and formulating proactive safety measures (Bangaru et al. 2021; Yu et al. 2019). These opportunities offered by sensor data analytics inform the need to prepare the future workforce with the skills to implement the technique in the construction industry. However, the application of wearable sensing technologies like IMUs in construction research often involves extensive programming constructs for developing analytics workflows. The insufficient emphasis on programming in civil engineering and related fields, where computing is frequently confined to off-the-shelf software, leads to a deficiency in exposure and training in programming skills (Talaat et al. 2022). Consequently, individuals in these disciplines may face challenges as they typically lack the domain knowledge for programming the sensor data analytics processes. Furthermore, scarce studies have explored pedagogical innovations to overcome the obstacles to equipping construction-engineering students with the needed skills. As a result, despite the evident importance of sensor data analytics, the challenge lies in new graduates possessing the skills required for efficiently analyzing the vast data generated (Khalid et al. 2023). The limited exposure of construction students to data analytics skills necessitates exploring alternative pedagogical approaches to address this skill gap.

End-User Programming Environment

EUP or EUD techniques have become particularly recognizable for their adaptability and added value in educational contexts. EUP is a subset of EUD that focuses on the programming process for developing programs.

Accordingly, installation, configuration, re-design, debugging, scaling, and execution are all included in the larger variety of techniques that support the whole software development life cycle under the umbrella of EUD (Coronado et al. 2021). When adopting a programmable platform for instructional purposes, a significant challenge is to minimize the requirement for users to possess extensive programming knowledge. BBPEs are a notable aspect of EUP, where the coding process is replaced with a simplified approach that utilizes visual blocks instead of traditional syntactical text-based coding (Skorik 2022). BBPEs, particularly for users without prior programming expertise, provide a straightforward and approachable coding experience with a visually driven programming interface. BBPEs provide users with flexible drag-and-drop capabilities by using interactive blocks that represent codes and programming notions. These approachable traits make it simple for people to understand and apply complex computational operations (Rough 2018). BBPEs allow users the ability to dwell on the logic, structure, and functionality of their algorithms by prioritizing semantics ahead of syntax and other programming language complexities (Bau et al. 2017). BBPEs have proven to be highly advantageous in bridging knowledge gaps in a variety of academic subjects, including chemistry, physics, robotics, cybersecurity, and data science, allowing learners to acquire domain-specific knowledge while improving their CT skills (Glas et al. 2023; Rahaman et al. 2020). Extensive research supports the positive outcomes resulting from the integration of domain-specific and CT skills using BBPEs (Gupta et al. 2017; Sarmento et al. 2015; Tawfik et al. 2022). However, with the high degree of customizability, the evaluation of the usability of the BBPEs stands out as an important procedure for ensuring the development of optimal learning outcomes (Karakasis and Xinogalos 2020; Rijo-García et al. 2022).

Theoretical Framework

The development and usability evaluation of InerSens, a BBPE, draws its theoretical underpinning from the Learning for Use (LfU) and can be viewed from the lens of Cognitive load theory (CLT). LfU lays the basis for technological platforms intended to improve students' skill development and encourage deep understanding (Edelson 2001). The following four principles form the foundation of this theory: "(1) knowledge construction is incremental; (2) learning is goal-directed; (3) knowledge is situated; and (4) procedural knowledge needs to support knowledge construction" (Edelson 2001). The design of InerSens centered on a hierarchical workflow of prevalent data analytics techniques, promoting a goal-directed problem-solving approach and gradual knowledge acquisition. To offer researchers a basis for assessing task performance while utilizing authentic construction sensor data, strategic usability benchmarks were established. These benchmark tasks encompassed: i) information review, ii) data selection, iii) data manipulation, iv) defining activity, v) developing a risk assessment chart, and vi) results or chart evaluation. This way, the hierarchical arrangement guides learners through tasks, from basic data selection to complex risk analysis, offering analytics opportunities via block representations. As learners progress in their analytical journey, they utilize both original data and manipulated structures from earlier stages to move forward to the next step. This aligns with the principles of gradual and incremental knowledge acquisition highlighted in the first and fourth tenets of LfU theory. The structured workflow of the InerSens platform is also consistent with the second and third tenets of LfU theory, emphasizing that knowledge acquisition is goal-oriented and context-dependent. The LfU theory also integrates the CLT, which aims to optimize learning outcomes by managing cognitive load. CLT suggests considering working memory limitations to avoid overwhelming learners in instructional design. Therefore, the evaluation of the environment contributes to CLT by detecting both cognitive and usability factors.

METHODOLOGY

In this section, the methodology adopted for the development and usability of InerSens is described including the specifics of the experimentation, the participants involved, and the techniques employed for data collection and analysis (refer to Fig. 1). The evaluation is centered around comparing the usability of InerSens to that of the conventional platform, Microsoft Excel, which is a commonly used platform for similar data analytics tasks (see Fig. 2 for an overview of the workflow).

Development of InerSens

This section describes the design and development process of InerSens, which adopted the agile User Experience (UX) lifecycle methodologies (Hartson and Pyla 2012).

User research

In a previous study (Khalid et al. 2023), the authors identified the expectations of end-users and the industry's prerequisites concerning the utilization of sensor data analytics in construction education. Based on the results of the study, user needs were identified to define specific features for the system that align with user-centered design concepts (Hartson and Pyla 2012). This includes the key sensing technologies (e.g., IMU, laser scanner, GPS, RFID, drones, cameras) and their applications (e.g., safety, asset and productivity tracking, quality control, inspection, and verification).

Creation of design concepts

The development process for the InerSens interface involved an ideation and creation phase based on the findings from the user research. This phase included brainstorming, sketches, and reviews to generate concepts, which were then combined into preliminary wireframes (Hartson and Pyla 2012). The objective of the design was to establish a standard workflow for sensor data analytics aiming to teach students about ergonomic risk assessment (see Fig. 3).

To illustrate the workflow and required activities for executing data analytics tasks, wireframes were created as part of the design concept generation process. Furthermore, the researchers emphasized the need to create user personas for construction students, along with defining user classes, roles, workflow modeling, and tasks.

Prototyping

Using custom-designed blocks via Blockly, high-fidelity prototypes were created. In the beginning, blocks were constructed to carry out analytics tasks relating to risk assessment, such as data selection, manipulation, defining activity, and development of a risk assessment chart. The blocks underwent testing to identify any potential interaction design flaws, including the actions users would engage in and the data they would view to successfully proceed with the risk assessment workflows. The prototypes were made available to researchers for comment, allowing for the early detection of possible problems and areas for improvement before proceeding with a more intricate design of the high-fidelity prototype.

Overview of the InerSens platform

In the design of InerSens, the Model-View-Controller (MVC) architectural pattern was adopted which is widely employed in the development of web-based applications. The MVC architecture encompasses three essential layers: the model, the view, and the controller. Each layer has distinct responsibilities, as elaborated upon in the following sections (see Fig. 4).

The view component is responsible for rendering information from the model onto the Graphical User Interface or GUI, designed specifically for learner presentation. Beyond displaying data, it actively manages learner inputs and actions on the GUI, including sensor data and video recording uploads, block clicks, and block relocations. The View records user activities and forwards the inputs and events to the controller for further processing. Moreover, it presents various results, such as structured data, videos, and risk assessment charts, and also facilitates import-export functionalities. Within the view, various components, including the block menu, block workspace, code generator, and analytics visualizer, have been implemented using Cascading Style Sheets (CSS). Additionally, video playback is integrated using the HTML Video tag, with JavaScript employed to capture and exhibit video timestamps. The model undergoes updates based on modifications made by the controller, reflecting corresponding changes in the information presented within the view. The controller acts as the intermediary between the model and the view. It responds to learner requests presented by the view in the GUI, such as selecting blocks, relocating blocks, and executing and recycling blocks. It utilizes Node.js libraries, namely Blockly and Data-Driven Documents (D3), to implement these functionalities. Blockly libraries contain blocks for performing various coding functions, while D3, a JavaScript toolkit, provides methods and modules for manipulating and displaying data using web standards like CSS, HTML, and SVG. The controller applies logic to execute essential operations, effectively translating user actions into meaningful processes. The model is tasked with storing user data in the MariaDB Server, a relational database management system. The Sequelize API facilitates interaction with the database, acting as a cross-platform JavaScript runtime environment mapper, simplifying the connection with databases such as MariaDB, MySQL, and SQLite.

Interaction with Inersens and Connections with CT Skills

Utilizing design frameworks to create block-based environments can lead to a significantly enhanced user experience (Karakasis and Xinogalos 2020). Consequently, an EUD-focused design framework was embraced, aligning with the requirements of risk assessment data analytics workflow. The researchers added the basic components that make up a web-based block environment based on the EUD design framework, which detailed the features to increase end-users CT skills within the EUD activity (Barricelli et al. 2023) (see Fig. 5) The framework was chosen for its dual benefits: improving students' CT skills and aiding in sensor data analytics tasks on the platform. This section outlines InerSens' key features for interaction and the relevance of CT skills to the platform's dimensions.

Block selection

The ability to select the necessary blocks from a menu comprised of numerous blocks is connected with the abstraction CT skill, which is the cognitive process of selecting the most important information about a system or situation while ignoring or simplifying the less important information (Calderon et al. 2022). For example, after dragging and dropping 'Read File' into the block workspace to import applicable raw sensor data into the interface, users can clean up the raw dataset using the 'Data Selection' block to preserve the important data required for the analytics while discarding the data that is unnecessary. As the process progresses, the user may pick the relevant blocks from the menu for each instance as the flow of the data analytics task demands (Fig. 6). At the outset, the concreteness of information enables users to effectively view the information, confidently select the necessary blocks, and carry out intended actions. The concreteness dimension in EUD environments refers to the ability of the environment to present domain-specific concepts tangibly, such as concrete events and conditions (Berti et al. 2006).

Block construction

The ability to assemble interlocking or container blocks in the block workspace, that store unit function blocks, enables users to leverage CT's decomposition skills to break down complex problems into attainable sub-problems (D'Alba and Huett 2017). The modularity dimension of the environment refers to the presence of diverse elements, blocks, or modules that assist end-users in decomposing problems and identifying the constituent pieces that contribute to their solutions (Barricelli et al. 2023).

Block structuring

The feature of structuring blocks allows the user to develop an analytics workflow of action sequences by creating logical links between the building blocks to generate solutions to targeted computational challenges. This occurs within the block workspace. A broad sequence of block structuring may include, for example, reading data, manipulating data, analyzing data, and viewing data. This characteristic is related to CT skill's algorithmic thinking, which is the way of creating and running algorithms to solve problems or carry out tasks (Shute et al. 2017). The structuredness component of EUD may be highlighted here since it relates to the environment's capacity to structure a solution in a step-by-step way, which also facilitates the process of linking the input and output of multiple processes (Barricelli et al. 2023).

Analytics results

The ability to view and examine analytics outcomes directly through the interface is associated with the evaluation skill of CT and the testability dimension of EUD. This functionality is facilitated by the 'Analytics Visualizer' panel (see Fig. 6) on InerSens, a dedicated workspace screen that offers visual feedback on the user's work. Users can analyze and examine the results in a separate panel, allowing them to scroll through the entire dataset and compare it with the original problem formulation and solving strategies. Moreover, the results can be simulated and visually presented, such as through a risk assessment chart, allowing users to assess the details of the risks that occurred at different stages of the activity in the chart per the construction activity video playback. The testability dimension involves assessing the results of activities within the EUD environment to determine the accuracy of a solution and compare it with other alternatives to optimize it, considering the available resources (Barricelli et al. 2023).

Export results

By providing the capacity to export findings in a variety of formats appropriate for specific purposes, users may efficiently interact and work with other stakeholders. The reusability component of EUD allows for the application of activity outputs in diverse contexts and simplifies sharing among end-users (Barricelli et al. 2023). This corresponds to CT's generalization skills, in which users detect patterns in previous solutions and apply comparable (potentially altered) techniques to distinct future challenges (Shute et al. 2017).

User Experience Evaluation

Participants

20 undergraduate students including 10 females and 10 males were recruited for the usability experiment. This sample size is similar to other learning environment-based usability studies utilizing eye-tracking analysis (Conley et al. 2020; Oyekunle et al. 2020; Zardari et al. 2021). The individuals are from civil engineering, building construction, and construction engineering management programs, and are at least 18 years old.

Data collection

This section describes the data collected during the experiment including demographic information, subjective data (e.g., system usability scale and perceived workload, verbal feedback), and objective data using visual attention.

Demographic data

Before commencing the experiment, demographic information, such as gender, and academic program, was collected from the participants via a pre-survey.

Overall System Usability Score (SUS)

In order to obtain subjective measurements to evaluate and compare the overall usability of InerSens in comparison to Excel for sensor data analytics, the study employed the SUS questionnaires. Participants used a 5-point scale, from strongly disagree to strongly agree, to score the 10 items consisting of 5 positive (odd-numbered) and 5 negative (even-numbered) statements, all centered on users' perceived system usability. Odd-numbered SUS items assess user inclination for frequent usage and evaluate ease of use, function integration, rapid learning, and confidence in system use. Conversely, even-numbered items gauge perceived complexity and measure self-sufficiency in technical support, consistency, and the learning curve. Within the context of evaluating sensor data analytics interfaces, these elements collectively offer evidence of user preferences, efficiency, and the comprehensive usability of the interfaces examined in this study. Following each round of tasks (with and without InerSens), participants were asked to complete the SUS questionnaire to gauge their perception of usability.

Perceived workload

The NASA-TLX questionnaire was employed to assess the perceived workload during task performance. The TLX consists of six subscales representing sources of workload namely: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration Level. These subscales are typically used to measure cognitive load in learning environments (Gerjets et al. 2004). Mental demand measures how much brain activity such as looking, thinking, and remembering is needed while using a learning environment. Physical demand measures the level of physical effort. Temporal demand measures time-related pressure from the task. Performance measures the effectiveness of task completion. Effort, on the other hand, measures how difficult learners must work to seek and understand the contents of a learning environment, and frustration measures how irritated discouraged, or stressed learners feel when interacting with a learning environment.

Visual attentional resources

Eye-tracking was used to assess the participants' visual attention while interacting with the platforms. Eye tracking data were collected using the Tobii Pro Glasses 3 eye tracker. The device has a sampling frequency of 50 Hz. Fixation duration and fixation counts were collected. Longer fixations relate to difficulty in extracting information or it means the media is more engaging (Wang et al. 2014). A higher fixation count relates to less efficiency in search (Wang et al. 2014).

Verbal feedback

Semi-structured interviews were conducted with the participants to obtain their feedback about their experience with using InerSens and Excel for the analytics task. The questions were structured to capture the challenges they encountered while interacting with the platforms and the features of the platforms that influenced their user experience.

Experimental Procedures

Participants were assigned to both the Microsoft Excel condition and the InerSens condition for performing data analytics tasks allowing users to reach comparable conclusions across conditions. The experiment employed a repeated measure within-participant design for comparisons where the evaluation of a new block-based tool (InerSens) was compared to Excel, considering Excel's common use among students in academic programs, whereas users of other software may have diverse levels of experience or no experience at all. Given that construction-related students commonly employ established practices in data analysis and workflows using Excel, benchmarking against Excel aids in evaluating how well the new block-based tool integrates into these existing practices in terms of usability. This strategy gains support from related usability studies where block-based tools were developed with Excel workflows as their benchmark and for the purpose of comparison. Previous research on BBPEs has benchmarked data analytics tasks resembling Excel workflows, assessing their usability in comparison to Excel. Jansen and Hermans (2019) established Excel as a benchmark for usability comparison with XLBlocks, a block-based tool. While writing formulas in Excel often involves challenges such as misplacing parentheses, quotes, and commas, the study posited that a block-based formula editor, like XLBlocks, could aid spreadsheet users by minimizing syntax errors. XLBlocks revealed an advantage over Excel as it offers a fully equipped integrated development environment (IDE) for improving formula readability and facilitating structure recognition surpassing Excel's limited formula bar. Schaathun (2022) employed a comparable strategy, using Excel as a standard, to introduce a block-based visual programming environment. This add-in enabled end-users without programming backgrounds to establish variables and constraints, explicitly defining the data flow between spreadsheets. The objective, similar to InerSens' primary goal, was to focus on Excel end-users and introduce visual programming to improve the usability of data analysis. Each participant's involvement in the experiment lasted approximately two hours, with a designated break of 20-30 minutes between tasks to allow for rest and refreshment.

Tutorial

Before the experiment began, participants received accessible tutorial materials and underwent a 15-minute practical demonstration to familiarize themselves with the task workflows and platform components (Ramoğlu et al. 2017). The tutorial and demonstration covered analytics tasks for both Excel and InerSens conditions. Following the approved Institutional Review Board (IRB) protocol, participants were initially presented with the informed consent form, and their pre-survey responses were documented.

Apparatus

To ensure uninterrupted operations, computer systems were configured accordingly. Participants used a high-performance desktop computer for task performance, while additional hardware and software (such as eye tracking) were employed on a separate laptop for data capture. Participants were situated in a controlled environment to maximize comfort and minimize distractions. Detailed instructions were provided to participants regarding the eye tracking procedures utilizing Tobii Pro Glasses 3. Calibration was conducted to ensure accurate measurements, and data recording commenced once satisfactory calibration was achieved. To set up the experiment, computer systems were configured to run the evaluated platforms. Hardware requirements and software versions were thoroughly tested beforehand to ensure consistent and uninterrupted operations for all participants. Participants performed the tasks on desktop computers equipped with high configurations, while a separate laptop with eye-tracking software and connected hardware was utilized for continuous monitoring of data recording. This setup allowed for the display of eye movements overlaid on the screen for real-time monitoring. Participants were positioned in a controlled setting to assure comfort, uniformity, and the elimination of unwanted distractions or discomfort. A briefing on collecting eye-tracking data using Tobii Pro Glasses 3 was provided to participants. The trackers had been cleaned and adjusted with different nasal bridges before use to ensure an appropriate fit for each participant. Calibration procedures were carried out before the assessment to ensure reliable eye-tracking readings, and recording began only once acceptable calibration was achieved.

Tasks

The tasks in this study involved interacting with pre-recorded construction activity information, including video recordings and raw IMU sensor data in both Excel and InerSens. Participants processed the sensor data and developed risk assessment charts from the construction activity information. An overview of the performed list of tasks on both platforms can be found in Table 1.

The tasks specified in Table 1 were derived from a methodology rooted in the principles of ergonomic construction risk assessment. This method employs posture angles to assess ranges of motion, enabling the calculation of ergonomic risk levels (i.e., low, medium, high) for identifying awkward postures in construction using IMU sensor data (Akanmu et al. 2020; Gonsalves et al. 2021). The employed methodology focused on tasks involving repetitive subtasks and dynamic postures, based on the postural ergonomic risk assessment classification by Chander and Cavatorta (2017). For data collection, the smartphone's built-in IMU sensor was attached to the target body part (i.e., trunk). Collected data included time-stamped acceleration, angular rotation, pitch data, and an external video recording of the activity (with a secondary device). For validation and the extraction of observational details regarding subtask timing and cycle count, the time-stamped data could be cross-referenced with video-recorded activity to ensure accuracy. A segment of a manual lifting activity, which encompassed three subtasks (lifting, walking, placing) spanning over two repetitive cycles was selected for the participants' analytics performance. For subsequent analysis, the pitch data and its corresponding timestamps were extracted. Pitch data, initially in Radians and later converted to Degrees, facilitated the computation of body segment orientation from the neutral plane. When defining the activity, participants were instructed to label subtasks based on their observations while reviewing the recorded video. Following defining each sub-task categorized for its corresponding data portions, risk impositions on body segments during each subtask were computed using frequency distribution as a percentage of the task duration resulting in task-specific histograms. Bin values were defined as thresholds for ergonomic risks, with corresponding angles classified into low, medium, and high-risk categories (see Table 1: Development of risk assessment). Examples of awkward postures could be when the target body part registered data points inside of the medium or high-risk thresholds. This resulted in the compilation of data from all subtasks into a unified chart, forming stacked bar columns to visually illustrate unique risk levels associated with specific tasks. For end-user evaluation purposes, plotting each subtask against duration as a percentage of the total cycle time served as a reference for comparing the risks posed by different subtasks in the final output, aligning with the actual activity. While the abovementioned methodology was adopted for Excel, the integration of similar tasks into InerSens involved an additional considering CT skills. For details of workflow integration and interaction design considerations within InerSens, refer to the 'Interaction with InerSens and Connections with CT Skills' section.

Data Analysis

To analyze the data collected from the SUS and NASA TLX questionnaires, both conditions (Excel and InerSens) were treated as ordinal variables. On the other hand, the eye-tracking data was considered as continuous. Shapiro-Wilk test was employed to assess the distribution of the data, revealing a departure from normal distribution in the majority of cases. Therefore, Wilcoxon Signed-Ranks Tests (WSRT) were utilized to examine the presence of statistically significant differences between paired observations. The pair-wise comparison of dependent variables included SUS, NASA, and eye-tracking measures as these were the measurements being compared between the two conditions. The independent variables are the conditions themselves, which refer to the two repeated conditions under which the measurements were taken. Significance was determined at a p-value of less than 0.05. Descriptive statistics such as mean, median, and standard deviations were considered.

System Usability Scale

The SUS scoring procedure consists of two steps: assessing each participant's responses and determining the mean score for all participants. Individual Scoring: For odd-numbered questions, subtraction of 1 from the user score. For even-numbered questions, subtraction of the user score from 5. The final SUS score for each participant was obtained by multiplying the sum of these scores by 2.5. (Sauro 2011). To calculate the mean SUS score for multiple participants: The total SUS scores of each participant were added up. Then, the sum was divided by the number of participants (Derisma 2020).

NASA-TLX

The NASA-TLX survey data comprises subscales for mental, physical, and temporal demands, along with performance, effort, and frustration (Hart and Staveland 1988). The overall TLX or workload score was computed using the unweighted average of the sub-scores, as it was discovered to offer higher sensitivity and reliability in comparison to the weighted average (Ikuma et al. 2009). Consequently, no attribute weights were allocated to the sub-scales and the raw scores were utilized.

Eye-tracking

To gather eye-tracking measurements, dynamic Area of Interest (AOI) and metrics tools were utilized. The AOIs in eye-tracking, represent specific areas of the user interface that are pre-defined by the researchers for focused metrics extraction (i.e., fixation) and analysis. AOIs can be used to examine participants' gaze behavior and understand visual attention dynamics in user engagement with digital interfaces (Lei et al. 2023). Six benchmark activities, identified as essential stages in both task performance scenarios (i.e., task workflows in Table 1), served as a comparable basis for mapping AOIs. Fixation-related metrics were recorded for each task step by activating AOIs at specific times. The dynamic AOI functionality ensured precise gaze data recording even when AOIs moved out of range due to head movement. Total fixation duration and total fixation counts in the AOIs were extracted from Tobii ProLab to understand the participants' visual attention to specific AOIs. These metrics also served as indicators of cognitive load and the platform's usability during task performance (Borys and Plechawska-Wójcik 2017).

Verbal feedback

After de-identification through random number assignment, NVIVO 14 software was utilized for qualitative data analysis. Open coding was employed to identify themes from relevant comments in the participants' responses, following guidelines by Saldaña (2009). Common themes were clustered and coded based on context alignment (Hsieh and Shannon 2005). To ensure consistency, common themes were cross-referenced with the original transcripts. Researchers achieved credibility through consensus on code interpretation (Miles et al. 2018; Robson and McCartan 2016). Inter-rater agreement for codes and themes was confirmed independently through two researchers based on a Cohen-Kappa score of Excel: 0.8125 and InerSens: 0.966, both showing substantial agreement.

RESULTS

The sections present a breakdown of the participants and results of the comparison of the SUS score, cognitive load and eye-tracking, and verbal feedback for InerSens and Excel:

Demographics

The demographics of the participants are shown in Table 2. The study had an equal proportion of male and female participants. More than half of the participants were in the civil engineering program.

Usability

According to the SUS score, Excel achieved 75.25, indicating a grade B in perceived usability, while InerSens surpassed expectations with a score of 82.25, obtaining a grade A. The grading scale places A above 80.3, B in the range of 68 to 80.3, C at 68, D between 51 to 68, and F below 51 (Sauro 2011). Using the mean scores, all measurements for each SUS subscale were compared between the InerSens and Excel conditions (see Fig. 7). ']*' is used to indicate the statistically significant different ($p < 0.05$) groups.

Cognitive Workload

Fig. 8 illustrates the comparison of calculated means for all subscales and the overall averaged TLX score for both conditions. The WSRT indicates a statistically significant difference in the mental demand and the overall TLX score for the two conditions. InerSens resulted in lower mental demand and overall TLX score compared with the Excel platform.

Eye-tracking

Fig. 9 illustrates the comparison of calculated means and the WSRT of the overall fixation duration (in seconds) for both experimental conditions, averaged across all individuals. The participants' cumulative time spent fixating on the designated AOIs is represented by the total fixation duration. The X-axis indicates the AOIs, while the Y-axis represents the fixation time expressed in seconds. The WSRT test shows that there was a statistically significant difference in the total fixation duration at the data selection, developing risk assessment, and chart evaluation in the two conditions.

Fig. 10 showcases the mean of the total fixation count and the WSRT test of participants on each AOI to compare the average number of times participants fixated on specific AOIs. The statistical results for the total fixation count show there was no statistically significant difference at the information review and defined activity AOIs. InerSens resulted in higher fixation counts in the rest of the AOIs except in the AOI related to the development of risk assessment.

The amount of time spent doing analytics tasks as a percentage of the entire task completion time or total visit duration to examine the allocation of attention is presented in Fig. 11.

Verbal Feedback

Following their participation in both data analytics conditions, participants were questioned about the challenges they encountered while interacting with the interface components and workflow of the analytics platform. Additionally, they were prompted to highlight salient features of the environment that influenced their user experience. Furthermore, participants were asked to provide suggestions for enhancing the two (2) learning environments. Figs. 12, 13, and 14 present the codes, themes, and frequencies of each code.

Advantages

Based on the notion of advantages, participants highlighted more instances for InerSens than Excel. Some examples of comments provided by participants for InerSens were as follows: '*I was thinking it would be really useful, especially for visual learners because you could actually see what's happening*,' '*Yeah, I really enjoyed the video being able to get the data straight from the video*,' and '*I like that it has different categories of what you're trying to accomplish. I think if you gave someone who had never done Excel or this, gave them both things, I think they would be able to figure out what they're supposed to do based on this versus Excel*.' Additionally, participants also acknowledged the advantages of Excel, stating, '*I think that the built-in functions that you can use are helpful. They make it quicker*,' and '*I have always enjoyed about Excel is just it seems very organized*.'

Challenges

Regarding challenges faced in using InerSens' new interface, participants mentioned the following: '*Learning how to do it basically cause it's my first time using it*,' '*I was a little confused between the defined activity versus defining individual tasks*,' and '*Probably just trying to learn the new interface. Because I've never used anything like that before. So just figuring out where things are and it's not like Excel, I have experience with, but with this one, I didn't know how to get from A to B*.' Furthermore, some challenges encountered in Excel were noted by participants, including: '*I think the part that maybe frustrated me the most was when we were going down and finding the different times I had to scroll*,' '*continuously having to scroll all the way and like times, well, if it was only 20 seconds, if you're doing 20 minutes, it would take a lot more scrolling*,' and '*one thing in Excel that's always bothered me is the copy and pasting thing. I wish it was a little bit easier to copy and paste the same thing multiple times*.'

Suggestions

When asked about user-experience-related suggestions concerning data analytics task performance on Excel, participants provided the following responses: '*It should be integrated into one cohesive system, instead of having to switch back and forth between Excel and the video*,' and '*Especially when dealing with graphs and switching between tabs, it would be beneficial if the system updated periodically to keep the user engaged and motivated during the activity*.' Following their usage of InerSens, participants expressed a desire for user customization of panel sizes and positions. One participant remarked, '*Like trying to scroll down there way they can make it like so that people can choose whether they want it to be bigger or smaller*.' Another participant suggested a feature similar to Blue Beam software, stating, '*So you know, how Blue Beam has like, you can hide stuff on the sides, bottom, and top. Maybe you have like a tab that slid up, but it started off just the full left side of the screen being the block selection menu. If you wanted, you could slide it up as far as you want*.' Both Excel and InerSens had favorable usability attributes, yet participants' preferences seemed to gravitate toward some of InerSens' distinctive features. Participants particularly expressed enjoying InerSens' aesthetic elements and user-friendly interface while experiencing a variety of interface-featured advantages. Participants eventually acclimated to the new interface despite early difficulties in navigating through InerSens due to unfamiliarity. In Excel, despite being straightforward, some tasks were repetitive (i.e., copying and pasting values, and scrolling through data), leading to frustration among the participants.

DISCUSSION

Usability

The SUS scores show that InerSens has a higher level of usability compared with Excel. This suggests that the majority of participants perceived InerSens to be more usable than Excel. The typical difference in the usability of the two systems was subjected to granular analysis on the effects of InerSens and Excel on each sub-dimension of usability to understand where they differed. The analysis showed statistical significance ($p<0.05$) in only two usability subscales. First, the participants strongly agreed that the InerSens platform has more well-integrated functions, and task performance in Excel was perceived as more unnecessarily complex. InerSens was perceived to be slightly better or similar in other subscales that considered anticipated usage frequency, ease of use, support requirement, system inconstancy, quick learnability, cumbersomeness, confidence in the system, and requirement of pre-learning. This highlights a favorable inclination toward the block-based platform over Excel, particularly with regard to alleviating specific usability issues and user requirements associated with implementing such platforms in context. The sensor data's proprietary formats demand Application Programming Interfaces (APIs) for accessing semantic relationships and the lack of convenient dataset controls can make inferences challenging while necessitating repetitive Excel procedures. These perceptions of Excel could have made it more challenging for users to understand and navigate the system effectively and also to acquire the necessary knowledge and skills to use it efficiently for sensor data analytics. This is why construction sensor data is analyzed using block representations of specific actions which makes InerSens for analyzing sensor data significantly more user-friendly than the traditional tool. This can be attributed to the flexible nature of block-based environments which makes it simpler to use for construction students. Similar results from research studies have repeatedly shown that BBPEs have fair user-friendliness, which has produced favorable assessments in terms of usability (Dawoud et al. 2021), usefulness, user satisfaction (Calderon et al. 2022), and quick learnability (Rough 2018). This signifies that the learning platform was efficient and effective enough to achieve the study's goal in terms of usability.

Cognitive Load

The subjective cognitive load of both platforms indicated that overall InerSens was perceived to be 46.11% less cognitively demanding compared to traditional Excel, which is consistent with research showing that block-based platforms typically lead to lower cognitive load compared to traditional text-based languages, as measured by the NASA-TLX questionnaire (Glas et al. 2023; Pratidhina et al. 2021). Although not statistically significant, InerSens has lesser demand in all other sub-dimensions, including performance, temporal demand, physical demand, effort, and frustration.

The code generation within InerSens was perceived as somewhat confusing by construction students who visited it and attempted to understand it. Nevertheless, the block-based programming feature ultimately conferred its prime advantage, as it obviated the need for manual code script modifications to accomplish students' data analytics tasks. This approach contrasts with traditional programming, which typically tends to impose a higher cognitive load sourcing from increased complexity (Unal and Topu 2021). However, some participants reported that they did not notice the lines of code in InerSens. Instead, they found it more efficient to streamline their workflow by visually organizing representative blocks, thereby diminishing cognitive demands. This can be attributed to construction students' limited proficiency in independently programming large volumes of sensor data. The positive outcomes can be seen as an indicator of the effectiveness of BBPE, suggesting that programming was no longer perceived as the challenging aspect of programmable artifacts (Weintrop et al. 2017).

Visual Attention and Impact on Overall User Experience

The eye-tracking data was employed to examine objective metrics when utilizing both platforms. The results show that four out of the six tasks of the InerSens workflow (i.e., information review, data selection, manipulation, and chart evaluation) in the total fixation duration were higher compared to Excel. Among these four tasks, data selection (p-value<0.0020*) and chart evaluation (p-value<0.0001*) were found to be statistically significant. Despite the differences, the total fixation duration averaged across all participants remained lower for InerSens than those observed in Excel throughout the entire workflow. A similar trend was observed in the comparison of the mean of total fixation counts.

For instance, in the 'Information Review' step, participants were tasked to access local files containing raw IMU data and activity video recordings. InerSens interface combined video and data on one screen, encouraging participants to interact with various elements throughout the step (i.e., play the video, scroll through the imported data, and reposition the blocks to see actions). In Excel condition, participants chose to quickly move on to the next task after a brief tutorial, possibly due to their familiarity with Excel. On the other hand, given that this is the first time most of the participants encountered the block-based tool, InerSens, the verbal feedback revealed that learning the new interface was a recurring challenge. This challenge aligns with a study on teaching learners how to program robot movements with block-based programming, where participants spent considerable time on the task due to their unfamiliarity with the block interface (Weintrop et al. 2017). A consistent trend was observed in the data selection, data manipulation, defining activity, and chart evaluation AOIs, where InerSens also exhibited longer fixation durations and higher fixation counts. Experiencing challenges in the initial stages of using InerSens may contribute to potential interaction and engagement issues. Hence, streamlining the onboarding process for BBPEs like InerSens can enhance users' efficiency in task execution. Potential improvements can be achieved by implementing more detailed tutorials and training, integrating interactive guides within the interface, and refining user controls aiming to assist users in comprehending the tool's functionality and navigation more effectively. Additionally, implementing real-time feedback mechanisms on user interactions, such as tooltips and visual cues, can guide users through the InerSens interface, fostering a more supportive learning environment.

However, as participants gained familiarity with the InerSens interface over time, they started to view it as intuitive. This corresponds with the findings from Mountapmbeme et al. (2022) where users initially faced challenges but eventually found the blocks and connections intuitive as they worked along the subsequent tasks. However, the increased number of fixations in InerSens during the ‘Chart Evaluation’ step should be attributed to its interactive interface rather than to participants still learning the new interface. Since this was the final step of the analytics process, participants can be assumed to have already gained some familiarity with the InerSens platform. Participants voluntarily spent more time evaluating the chart and construction activity video as InerSens facilitated real-time chart visualization synchronized with videos, where chart elements changed colors as the subject's range of motion altered. This indicates that engagement is boosted when students interact with their own analytics artifacts through interactive visualization. This aligns with the findings of Ruiperez-Valiente et al. (2022) suggesting that learning is enhanced when sensor data is graphed in real-time as opposed to analyzing the same physical phenomenon (motion) asynchronously. While in Excel, users could only evaluate static charts.

In InerSens, a significant reduction in both fixation durations (p-value<0.0001) and fixation count (p-value<0.0001) only occurred during the 'Develop Risk Assessment' step, where participants utilized their prepared sensor data to create the final charts. Participants spent only 9% of their visual attention span in InerSens on this specific step, compared to 45% in the corresponding Excel condition (see Fig. 11). This supports InerSens' efficiency in achieving comparable or better outcomes than Excel with shorter fixation durations or task completion times which are regarded as a key metric indicating the overall information processing time in user interactions (Cowen et al. 2002). This was expected because InerSens streamlined chart development with block functions, eliminating the need for users to switch between spreadsheets and optimizing repetitive steps in histogram creation. Similarly, Punchoojit and Hongwarittorrn (2017) reported that reduced task completion time, as an indicator of usability may signify enhanced work efficiency and ease of learning, leading to overall improved productivity. The observed pattern can also be seen as an indication of lower cognitive load and an increase in efficiency in the InerSens condition since there is minimal temporal and spatial segregation of information, implying a smoother and more efficient cognitive process (Aryadoust et al. 2022; Sweller 1988). On the other hand, the repetitive transitional efforts observed in the corresponding Excel condition made task completion time prolonged due to such repetition of steps which can alter perceived fatigue (Käthner et al. 2014). Furthermore, the findings of Tzafilkou and Protogeros (2017), also support that significantly higher fixation duration on a specific point may lead to doubts about the predicted outcome or performance of a completed action, potentially affecting the perception of the system's usefulness. Di Stasi et al. (2011) also indicated that frequent transitions between different windows and platforms, coupled with a greater number of task steps, can result in fluctuations in the attentional state which may increase cognitive load and attentional processing demands.

In terms of average time spent per step, InerSens had a fixation duration of 119.63 seconds. Excel, on the other hand, had a 26.43% higher fixation duration, averaging 162.6 seconds per step. Additionally, Excel had an average of 21.82% more fixation counts per step than InerSens, indicating that participants spent more time fixating on elements within Excel for each step compared to InerSens. This increased fixation count suggests that users might have had a less efficient search for information strategy with Excel in comparison with InerSens (Wang et al. 2014). Cowen et al. (2002) indicated that fixations are highly sensitive to usability, with the potential for a 46% to 67% increase in fixations from the 'best' interface to the 'poorest' interface. This highlights a strong connection between fixation frequency and interface usability which elucidates the lower usability rating and the higher cognitive load rating by participants in the Excel condition.

This finding underscores the importance of considering the time allocated to each step in BBPE design, as it directly affects end-users' attention demands, usability, and cognitive load perspectives. Construction students, as the end-users, favor a balanced approach over heavily emphasizing attentional efforts on a single analytics step. As a guideline, BBPE should aim for an even distribution of attention demands across key steps to enhance usability, manage cognitive load, and improve learning outcomes for the construction workforce, who can apply their knowledge of sensor data analytics in the practical field.

CONCLUSIONS

This paper presents an experimental study focused on developing a block-based programming platform for learning sensor data analytics in construction engineering programs. The research assesses the tool's effectiveness in supporting sensor data analytics by evaluating users' subjective feedback and objective behavioral metrics. Both Excel and InerSens were acknowledged for their user-friendliness and advantages; however, certain unique features in InerSens led to a preference shift as the medium for this particular type of data analytics task. Three characteristics of the block-based approach, in particular, emerge as potential reasons for this outcome. These are dynamic chart visualization (AOI- chart evaluation), optimized analytics tools (i.e., 4 panels of information feed for the user on one screen), and aesthetics of blocks (i.e., shapes and colors). The dynamic graphical chart in the blocks-based interface offers a compelling explanation for some observed differences in user behavior. The findings indicate that InerSens was slightly preferred over Excel, providing a more user-friendly experience with a lower cognitive burden and balanced visual attentional demands for sensor data analytical tasks. However, it did not show a significantly distinct competitive advantage compared to Excel. In some tasks, Excel allowed for faster performance, but the total fixation duration surpassed InerSens. Although four tasks in InerSens resulted in increased information processing or task completion time, it still resulted in an overall lesser fixation duration and counts as revealed through eye-tracking fixation analysis, and they did not lead to an overall negative perception of usability or cognitive load. Moreover, participants in InerSens were more easily focused on key information, leading to better efficiency in task performance compared to the use of Excel for sensor data analytics. The essential difference in usability stems from the system architecture and interaction design philosophy employed by these two platform types. Excel, functioning as a conventional spreadsheet software, adheres to a cell-based paradigm. On the other hand, block-coding-based platforms, exemplified by tools like InerSens, employ a visual and modular approach to data analytics. This involves assembling blocks that represent different task execution constructs, allowing users to advance by arranging these blocks in a logical sequence. Furthermore, as block-based tools support a high degree of customizability to meet domain-specific user demand, these tools can be embellished with separate panels (i.e., block workspace, visualizer, codes, and video playback) as needed to streamline the analytics tasks. The advantages of this approach become evident in terms of improved readability, reduced syntax errors and repetitions, and enhanced visual representation of the analytics structure.

LIMITATIONS AND FUTURE WORK

Certain limitations exist within this study, and these should be regarded as potential points for consideration in future research efforts. While the sample size (N=20) may suffice for identifying usability issues of the interactive interface, it could constrain the achievement of robust representativeness and the generalizability of findings to a wider construction population. For instance, the small sample size and the fact the data were collected in a single university may limit the generalization of findings specifically to a demographic or knowledge subgroup. In addition, the sample size presents a limitation for inferential analysis, potentially reducing statistical power and the detection of true effects or differences between conditions. Moreover, demographic factors such as the academic year of participants may not comprehensively capture all academic levels, particularly freshmen. Subsequent academic years could exhibit advanced exposure to introductory programming or data analysis courses, resulting in potential variations in interactions. These differences may influence the perception of usability and cognitive load. Consequently, future research endeavors will incorporate a balanced representation of participants from all academic years to ensure a more comprehensive understanding and a larger sample size to enhance generalizability across diverse demographics. In addition, although this research emphasizes the importance of well-defined scopes due to the EUP platform's customization for specific construction activity analysis, however, the findings may not be universally applicable to diverse data analytic tasks. Therefore, task-specific usability analysis is recommended for extracting a more accurate representation of the data to inform the design and development process. Future research will also explore alternative data analysis techniques, such as learning curve analysis, interaction analytics through mouse-tracking data, and utilizing objective indicators of cognitive load, such as electroencephalogram (EEG), to examine variations in brain activity related to cognitive load during analytics tasks associated with both conditions.

DATA AVAILABILITY STATEMENT

All data used during the study appear in the submitted article. All data supporting the study's findings are accessible from the corresponding author upon reasonable request.

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Table 1. Data analytics tasks completed by participants.

Task Workflow	Excel	InerSens
Sensor data and activity video review	• Open and review raw IMU data • Play and review video recording of the mimicked construction activity	• Import, open, and review raw IMU data from the local drive on view or analytics visualizer • Import, play, and review video recording of the mimicked construction activity into video playback display
Data selection	• Delete and only retain required data columns (i.e., retain timestamp and pitch data columns)	• Delete and only retain required data columns (similar)
Data manipulation	• Modify timestamp format using Excel formula (i.e., the difference between 41mm:27.6ss 41mm:28.1ss is 00mm:00mm.5s which matches with video recording timestamp format • Convert angle unit (from Radian to Degrees) • Adjust the orientation of the angle reference	• Convert angle unit (from Radian to Degrees) • Adjust the orientation of the angle reference
Defining activity	• Define data based on construction activity information (i.e., video recording, different tasks, timestamps, and cycles)	• Define data based on construction activity information (similar)

Development of risk assessment	• Define bin values as thresholds for different levels of ergonomic risks (i.e., <20°: Low risk, 20-60°: Medium risk; >60°: High risk) • Create histogram outputs based on the number of defined tasks within the activity (i.e., number of tasks*cycles = number of histograms) • Modify histogram's output with Excel formula (i.e., frequency to percentage) • Gather all histogram data into one Excel tab to develop stacked bar columns showing different risk levels associated with the corresponding tasks	• Select the body part affected • Define bin values as thresholds for different levels of ergonomic risks (similar) • Develop stacked bar columns showing different risk levels associated with the corresponding tasks
Chart evaluation	• Evaluate the chart and contributing data sources to conclude	• Evaluate the risk assessment chart • Select a specific task to view the dynamic visualization of the chart simultaneously with the video

Table 2. Participants' demographic information.

Category	**Demographics**	**Group** (N=20)
Gender	Male	10 (50%)
	Female	10 (50%)
Academic Program	Building Construction	4 (20%)
	Civil Engineering	9 (45%)
	Construction Engineering and Management	7 (35%)
Academic Year	Freshmen	0 (0%)
	Sophomore	2 (10%)
	Junior	9 (45%)
	Senior	9 (45%)
Programming familiriaty	Not at all familiar	10 (50%)
	Slightly familiar	5 (25%)
	Moderately familiar	5 (25%)

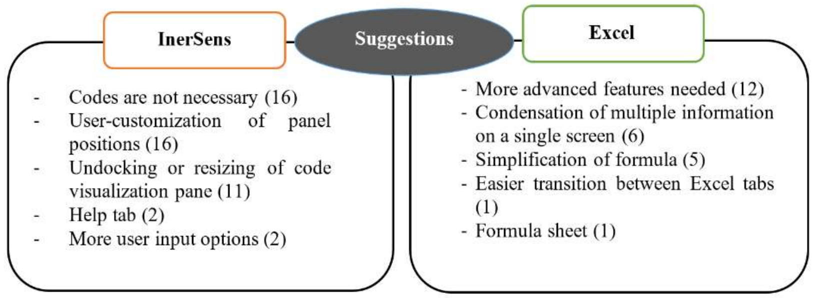

Fig. 14. Suggestions for InerSens and Excel learning environments.

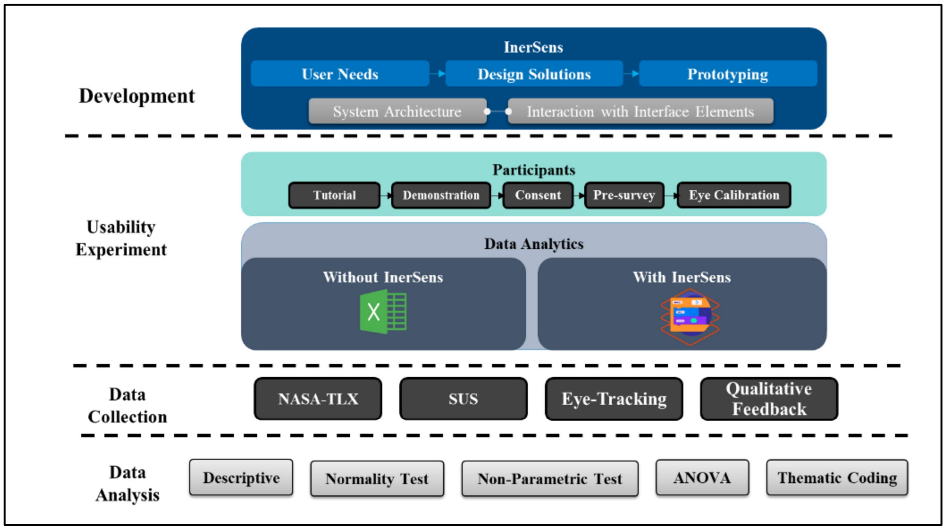

Fig. 1. Overview of research methodology.

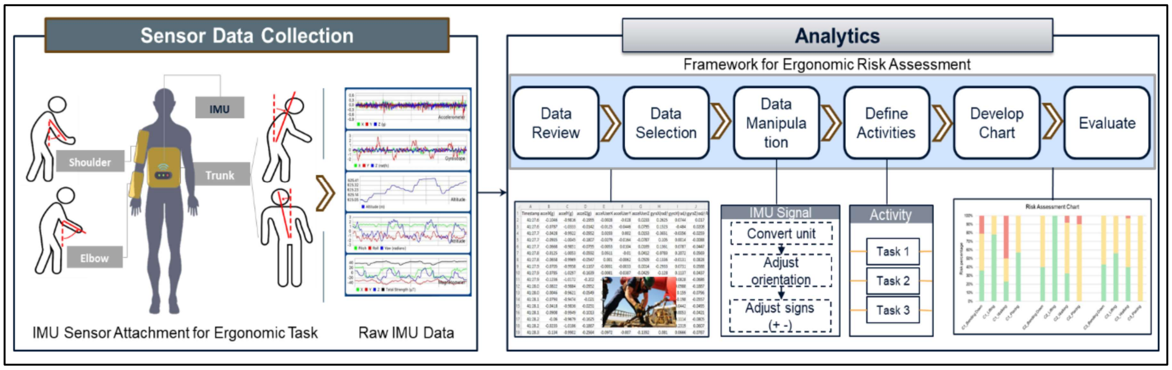

Fig. 2. Overview of data analytics workflow.

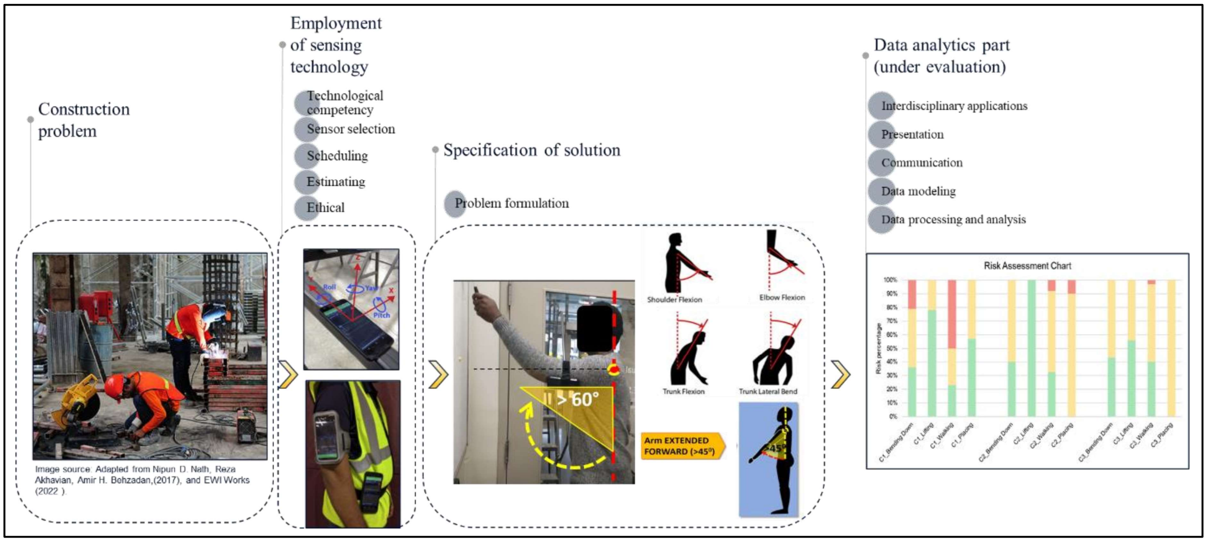

Fig. 3. Basic workflow for ergonomic risk assessment using IMU sensors.

Fig. 4 Click here to access/download;Figure;Fig. 4.pdf

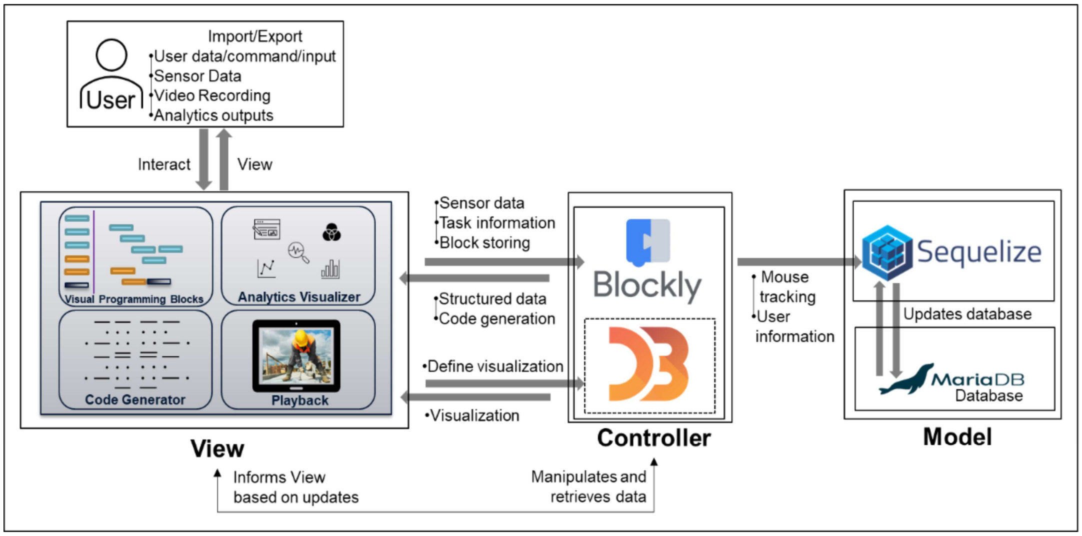

Fig. 4. System architecture of InerSens.

Fig. 5

Click here to access/download;Figure;Fig. 5.pdf

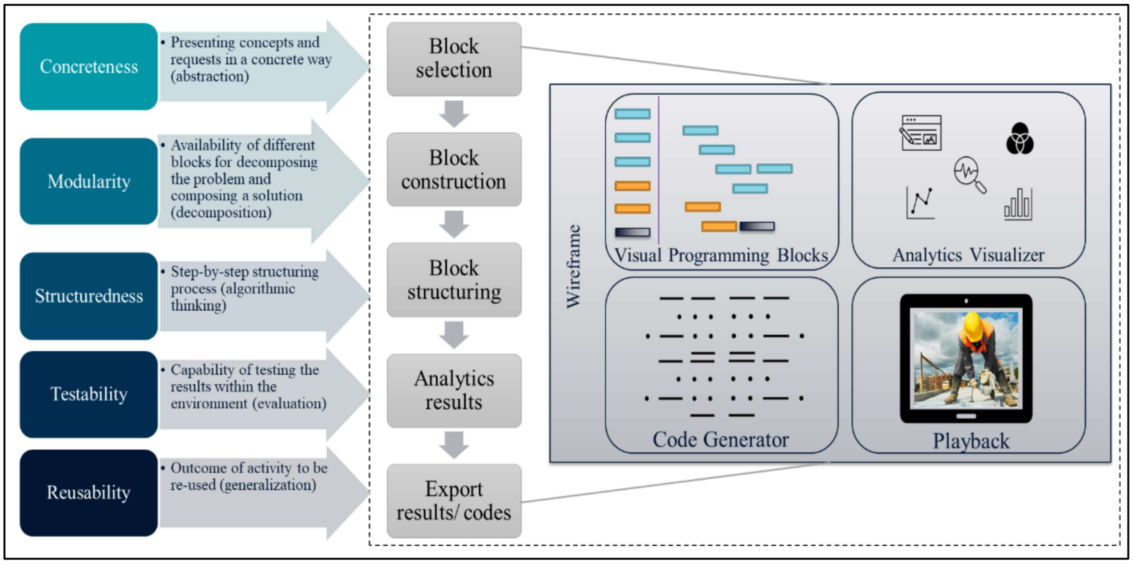

Fig. 5. Connections between EUD features and computational thinking.

Fig. 6

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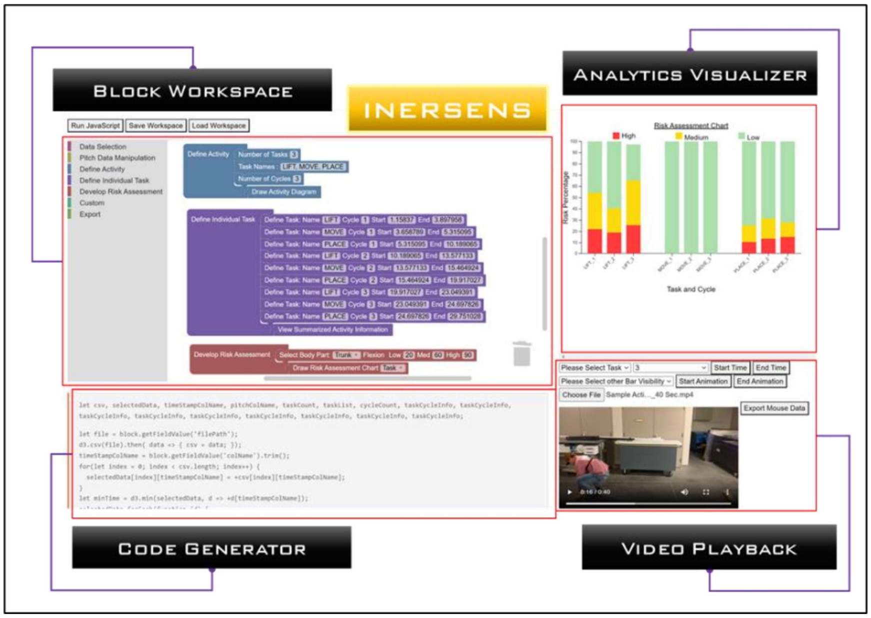

Fig. 6. InerSens interface.

Fig. 7 Click here to access/download;Figure;Fig. 7.pdf

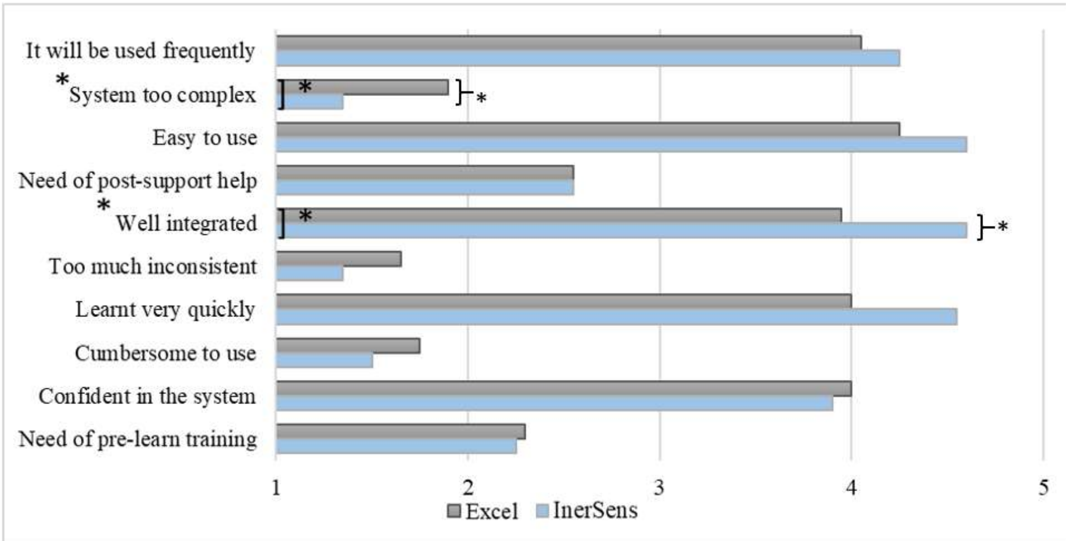

Fig. 7. Comparison of SUS sub-scales between the two conditions (rating: 1 = strongly disagree; 5= Strongly agree).

Fig. 8 Click here to access/download;Figure;Fig. 8.pdf

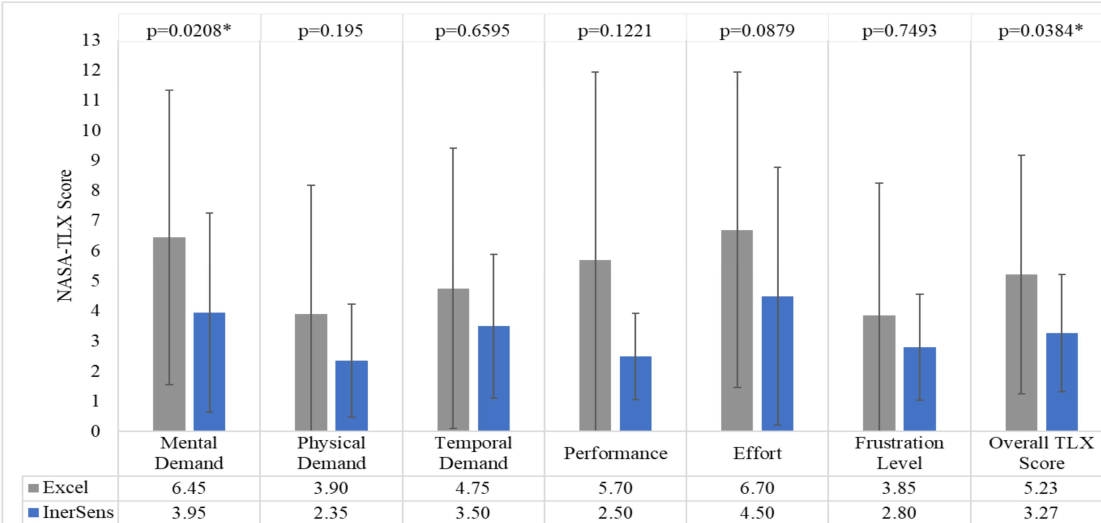

Fig. 8. Comparison of perceived workload (raw NASA-TLX) between the two conditions.

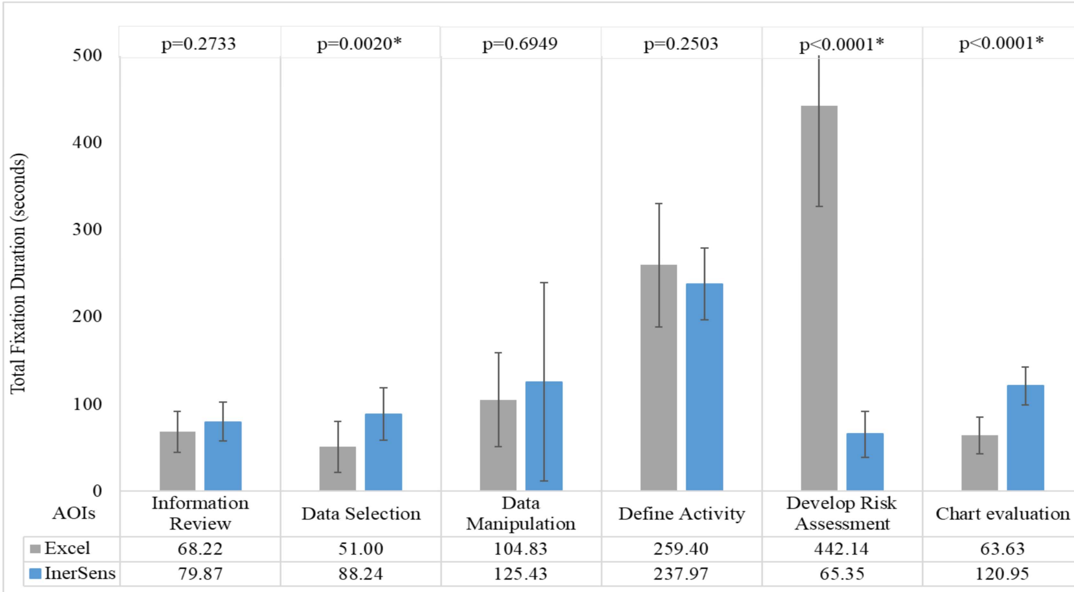

Fig. 9. Comparison of total fixation duration in specific AOIs for both conditions.

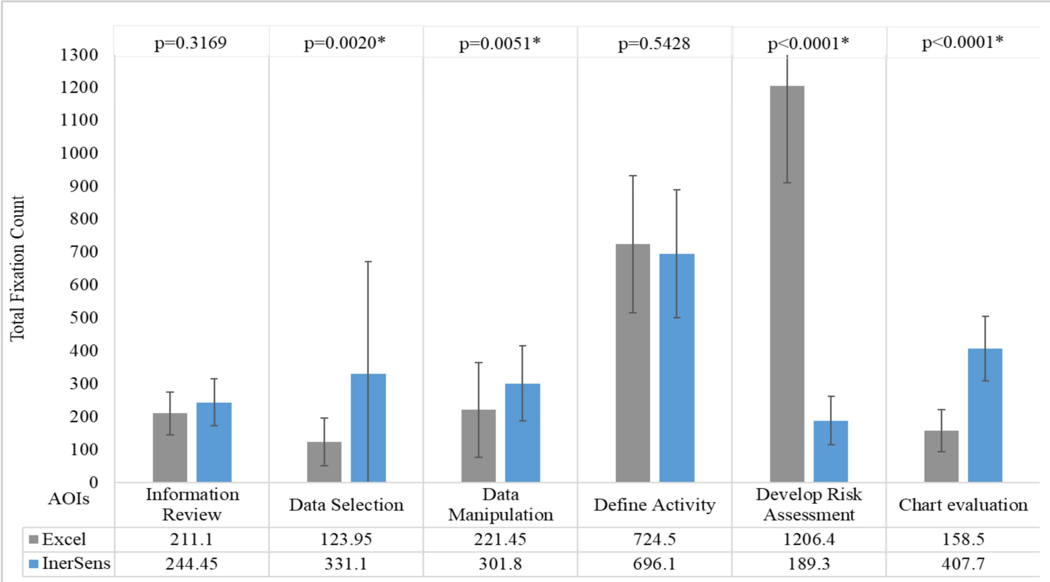

Fig. 10. Comparison of total fixation count mean in specific AOIs for both conditions.

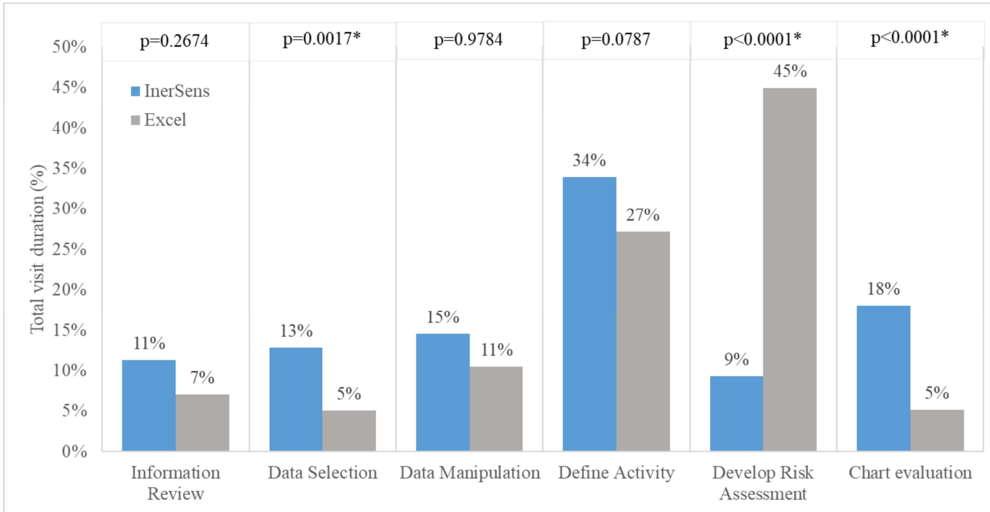

Fig. 11. Comparison of proportions of visit duration means of AOIs for both conditions.

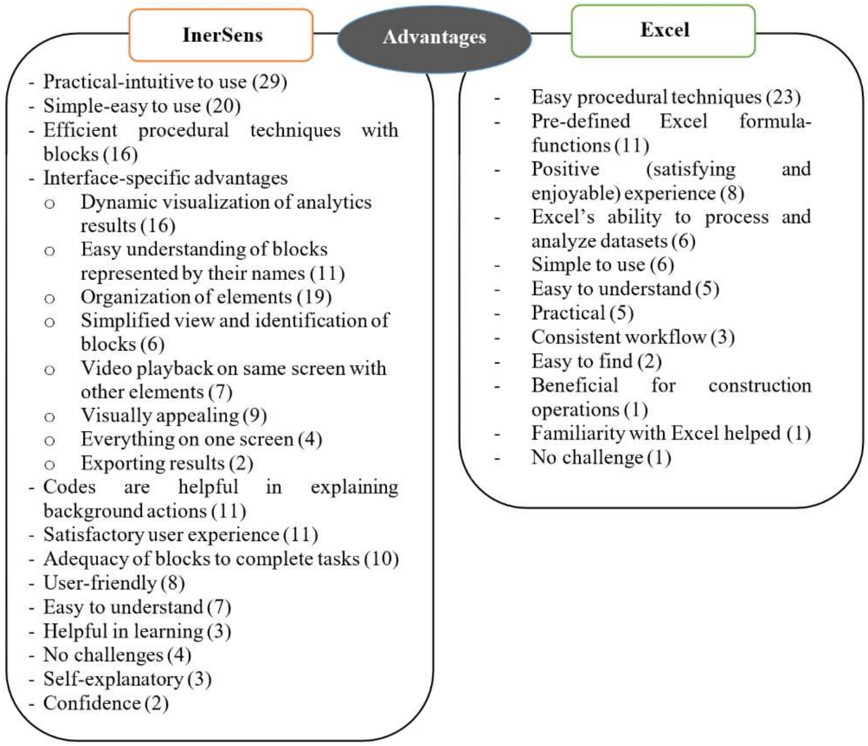

Fig. 12. Advantages of InerSens and Excel learning environments.

Fig. 13 Click here to access/download;Figure;Fig. 13.pdf

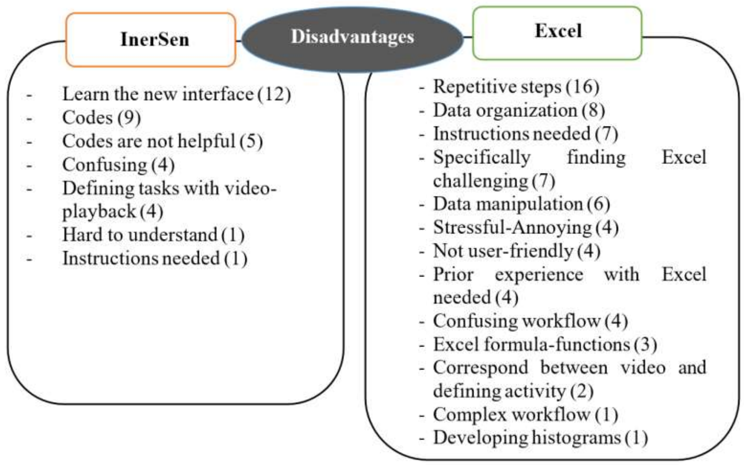

Fig. 13. Disadvantages of InerSens and Excel learning environments.