A Serious Game for Handwriting Training and Smart City Learning

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Abstract. Introduction: *Serious games can support learning by presenting complex concepts in interactive ways. In urban education, they have been used to introduce topics such as smart cities, which are difficult to teach in early education. In handwriting, serious games support the training of writing skills. Recent advances in artificial intelligence enable the analysis of handwriting, creating opportunities to support writing development.* ***Objective:*** *Develop a serious game for children aged 5 to 11 that introduces smart city concepts while strengthening handwriting skills using a convolutional neural network (CNN).* ***Methodology:*** *The research followed four main stages: definition of game mechanics, system implementation, training of a CNN for handwritten word recognition and an experiment, conducted with 14 participants.* ***Results:*** *The experiment indicates high engagement and positive usability perceptions. Participants were able to associate game elements with basic smart city concepts, while handwriting recognition showed moderate accuracy with high variability.*
Keywords *Serious Games, Smart Cities, Handwriting, Convolutional Neural Networks.*

1. Introduction

Digital technologies have increasingly influenced educational practices, enabling the development of interactive and engaging learning tools. Among these, serious games have gained relevance for combining entertainment with structured learning experiences [Abt 1970, Prensky 2003]. By offering interactive environments where players can experiment, make decisions, and receive immediate feedback, serious games promote active learning and can enhance motivation and knowledge retention compared to traditional approaches [Ren et al. 2024, Alotaibi 2024, Brandl and Schrader 2024].

Parallel to these pedagogical advances, discussions on urban development emphasize the importance of smart cities, which integrate technology, sustainability, mobility, and citizen participation to improve quality of life and optimize resource management [Gracias et al. 2023]. However, introducing these concepts to children is challenging due to their abstract and interdisciplinary nature, often requiring simplified and interactive strategies. In this context, serious games have been explored as tools to support the understanding of urban systems and smart city concepts through simulations and participatory learning [Cavada and Rogers 2019, Aguilar et al. 2021, Kurniawan et al. 2022].

Serious games have also been applied to handwriting practice. Handwriting involves fine motor coordination, spatial perception, and cognitive processing, contributing to communication and broader cognitive development [Piaget 2004]. Studies indicate that writing proficiency develops progressively in early school years, and difficulties may signal disorders such as developmental dysgraphia [Overvelde and Hulstijn 2011, McCloskey and Rapp 2017].

Recent advances in artificial intelligence, especially Convolutional Neural Networks (CNNs) for handwritten word recognition [Aires et al. 2026], enable automatic analysis of handwriting patterns. These technologies support the development of educational tools that assist learning and help identify difficulties such as dysgraphia [Dui et al. 2020, Dui et al. 2024].

The analysis of the literature highlights an important gap, although there are serious games focused on smart cities and others dedicated to handwriting learning, no solutions were identified that integrate both domains into a unified experience. Furthermore, most handwriting-focused applications emphasize low-level motor skills, such as letter tracing or isolated character reproduction, with limited attention to complete words or cursive writing. This separation reveals an opportunity to design educational systems that simultaneously support conceptual learning and literacy development. In addition, serious games that incorporate handwriting interaction can create engaging environments where children learn vocabulary and concepts while generating data that can be computationally analyzed [Maxim and Martineau 2008, Ren et al. 2024].

Therefore, this work presents the development of a serious educational game for children aged 5 to 11, designed to introduce smart city concepts while strengthening handwriting skills through word practice. Additionally, player and interaction data are collected to support handwriting pattern analysis and enable future research.

2. Related works

A literature review on serious games related to smart cities and handwriting learning was conducted, with the objective of identifying existing approaches that address these themes. The research was carried out in recognized academic databases, including IEEE Xplore, ACM Digital Library, Semantic Scholar, and Google Scholar, focusing on both methodological approaches and practical applications. The review revealed that, although there are several serious games that address smart cities and others focused on handwriting learning, no works were found that combine both elements into a single solution. Therefore, the analysis was divided into two domains: serious games for smart cities and serious games for handwritten manuscripts.

2.1. Smart cities

Among the games analyzed, *Metropolis* stands out as a simulation designed to encourage participation in urban planning processes. Therefore, Metropolis acts as a playful tool and as a space for reflection on the inherent complexity of smart city management [Aguilar et al. 2021]. Another example is *Serious Urban Play*, which was designed with a focus on education in urban spatial design [Stevens et al. 2014].

In addition, initiatives such as *Urban Shaper* explore gamification as a way to collect data on the perceptions and preferences of citizens about urban development

[Olszewski et al. 2016]. Finally, the game *CO2rdinates* promotes the co-creation of more sustainable cities by incorporating gamification elements into everyday activities, engaging citizens directly in sustainable urban planning [Chian 2023]. Table 1 presents a comparison of the main serious games related to urban planning, highlighting their target audiences, objectives, main features, and supported platforms.

Table 1. Comparison of serious games related to urban planning

Name	Target Audience	Objective	Highlight	Platform
Metropolis	Citizens, urban managers and students	Simulate collective behaviors in cities	Collective voting decisions	Desktop
Serious Urban Play	Middle and high school students	Teach urban spatial design	Interactive planning environment	Desktop/Web
Urban Shaper	Local community	Collect urban perception data	Citizen participation	Web/Mobile
CO2rdinates	Citizens interested in sustainability	Map CO2 emissions through missions	Real-world gamified actions	Mobile

2.2. Handwritten manuscripts

The *Kid Cursive* game was one of the first games to focus on teaching handwriting by exploring playful elements and child-friendly illustrations [Maxim and Martineau 2008]. [Dui et al. 2020] proposed the tablet application *Play Draw Write*, which allows the tracking of early handwriting skills during the pre-literacy stage. Continuing this line of research, [Dui et al. 2024] presented the game *Letter Tracing*, which combines handwriting teaching with automatic proficiency assessment using machine learning techniques. Table 2 summarizes the main characteristics of serious games related to handwriting learning.

Table 2. Comparison of serious games related to handwriting

Name	Target Audience	Objective	Highlight	Platform
Kid Cursive	Children in literacy phase	Teach cursive writing	Playful narrative and illustrations	Desktop
Play Draw Write	Preschool children	Assess early writing skills	Development of fine motor skills	Mobile
Letter Tracing	Children at risk of dysgraphia	Teach and evaluate handwriting	Use of machine learning models	Mobile

Analyzing the serious games described in this section, it was found that they did not address the topic of urban planning, one of the subjects covered in smart cities, for children and the handwriting games only addressed characters and not words. Therefore, the game proposed in this article integrates the themes of smart cities and handwritten word recognition.

3. Methodology

The development of the proposed serious game followed an iterative process structured according to the workflow presented in Figure 1. The process was segmented in four parts that describe the methodology process: the definition of game mechanics, system implementation, development of the handwriting recognition model, and experimental evaluation.

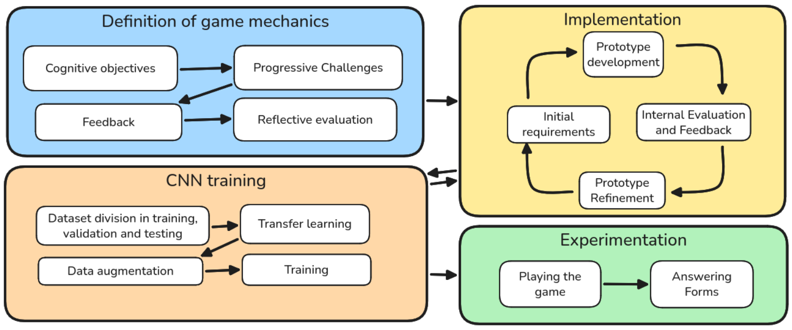

Figure 1. Diagram illustrating the whole methodology used in the research

3.1. Definition of Game Mechanics

The game mechanics were defined following the constructivist framework [Piaget 2004] and its operationalization in educational systems [Cunha 2013] by structuring the interaction into four components: objectives, challenges, feedback, and evaluation. These components were implemented directly in the gameplay to connect smart city elements with handwriting tasks. The relationship between smart city mechanics and handwriting activities was summarized in Table 3.

Table 3. Definition of smart city mechanics and handwriting tasks

Phase	Smart cities	Handwriting
Objectives	Introduce core urban elements and basic planning principles in a simplified city context	Associate each urban element with its corresponding word to reinforce vocabulary and meaning
Challenges	Place and organize structures in a grid while considering services, distance, and efficiency constraints	Write specific words to unlock elements, progressively increasing difficulty and complexity
Feedback	Provide real-time visual cues and a level summary based on city organization and efficiency	Validate handwritten input using a CNN model and indicate correctness to the player
Evaluation	Assess overall city layout considering organization, accessibility, and service distribution	Assess performance based on recognition accuracy of the written words

The cognitive objectives were implemented by associating each urban element with a word that must be written by the player, integrating handwriting into gameplay progression and reinforcing vocabulary and motor skills. Progressive challenges were designed as levels where players organize urban structures while producing the required handwritten words. The game incorporates planning concepts such as service placement and waste management, with performance affected by factors like accessibility to essential services. Complexity increases with new elements and constraints. Feedback is provided through visual indicators (colors, icons) and a star-based summary at the end of each level. Handwriting inputs are evaluated by a convolutional neural network to verify correctness. Reflective evaluation combines city performance and handwriting recognition results at the end of each level.

3.2. Implementation

The system was implemented following an iterative process based on evolutionary prototyping, as illustrated in Figure 1. Each component of the system was progressively developed, tested, and refined through successive iterations, allowing adjustments to both gameplay mechanics and technical modules throughout development [Brandl and Schrader 2024, Ren et al. 2024, Lee et al. 2024].

The implementation was carried out using the Godot Engine, resulting in an interactive application composed of multiple scenes, including a main menu, level selection interface, and gameplay environments, as illustrated in Figure 2. The core gameplay is based on a grid system in which players place urban structures using a side panel interface. A handwriting input module was implemented to allow users to write directly on the screen using touch interaction. The input is captured as an image and processed in real-time by the recognition system, following common approaches for digital handwriting acquisition and processing [Dui et al. 2020, Dui et al. 2024]. Based on the classification result, the system determines whether the corresponding construction is unlocked.

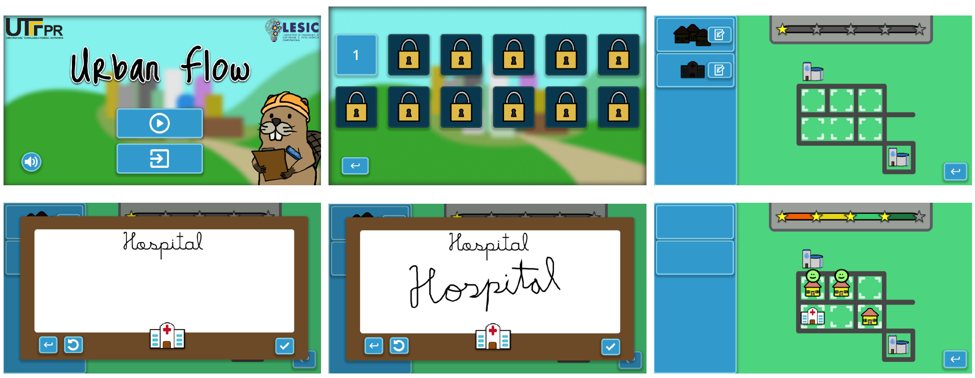

Figure 2. Screenshots of the serious game, showing the main menu, level selection and different parts of level 2, such as writing section and the city planning.

A data collection mechanism was integrated into the application to record user interactions, following common practices in serious games learning systems [Prensky 2003, Ren et al. 2024]. The system captures events such as clicks, drag-and-drop actions, and handwritten inputs, along with the predictions generated by the model. All collected data are stored in JavaScript Object Notation (JSON) format, where each session includes metadata such as a unique identifier, interaction time, and user profile information, including birth date and gender.

3.3. CNN Training

The handwriting recognition module was implemented using a convolutional neural network based on the architecture described by Aires et al. (2026), adapted for real-time inference within the game.

A transfer learning approach was adopted using MobileNetV2 pre-trained on ImageNet as a feature extractor. The top layers were replaced with a custom architecture composed of an additional convolutional layer with 256 filters, followed by batch normalization, global average pooling, and fully connected layers with dropout regularization. The model was configured to classify five words associated with game elements: recycling, sanitation, hospital, school, and housing. The dataset was obtained from previous works [Santos et al. 2024, Passos et al. 2025] and complemented with additional samples. The number of samples per class is presented in Table 4.

Table 4. Number of samples per word in the train dataset

Word	*Reciclagem*	*Saneamento*	*Hospital*	*Escola*	*Moradia*
Sample amount	40	40	40	36	33

An additional class containing random and non-meaningful inputs was included to enable rejection of invalid samples and reduce false positives, following [Ji et al. 2020]. The dataset was split into training, validation, and test sets using a stratified 60%, 20%, and 20% division, preserving class distribution. Input images were preprocessed and augmented using transformations such as small rotations, translations, zoom, and shear to improve generalization. Training was conducted for 35 epochs using early stopping based on validation loss. The model achieved a final training accuracy of 99.19% and a best validation accuracy of 88.68%, with training and validation losses of 0.037 and 0.422, respectively. On the held-out test set, it reached an accuracy of 84.21%.

3.4. Experimentation

A preliminary evaluation was conducted with 14 participants aged between 5 and 11 years, corresponding to the target audience of the proposed system. The distribution of participants by age is presented in Table 5.

Table 5. Participants' ages and gender

Participant	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
Age	5	6	7	8	9	10	11	5	6	7	8	9	6	7
Gender	F	F	F	M	F	M	F	F	M	M	M	F	F	F

The experiment was conducted in a controlled environment using two touch-based devices. Each participant interacted with the game individually using a stylus pen. Before starting, a brief explanation of the game mechanics was provided, including how to place buildings and how to perform handwriting input. Each participant completed an individual session lasting approximately 18 minutes.

After completing the session, participants answered a questionnaire composed of two types of questions: some required binary responses (yes or no), while others were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) [Jebb et al. 2021]. The questionnaire was structured into three categories: usability, smart city learning, and handwriting (Table 6). Usability covers metrics such as enjoyment, engagement, ease of use, prior experience, and replay intention while smart city learning assesses understanding of concepts and planning challenges, and in handwriting, task difficulty, and perceived recognition accuracy. Also, the software collected behavioral metrics related to user interaction: interaction frequency (M12), level completion time

Table 6. Questionnaire structure and aspects

Category	Question	Response Type	Metric
Usability	Did you like the game?	Likert scale	M1
	Is the game fun?	Likert scale	M2
	Is the game easy?	Likert scale	M3
	Have you played a similar game before?	Yes/No	M4
	Would you play it again?	Yes/No	M5
Smart city learning	Was building the city easy?	Likert scale	M6
	Did the game help you better understand smart cities?	Yes/No	M7
	Did creating cities help you understand the challenges of planning a smart city?	Yes/No	M8
Handwriting	Can you read and write?	Yes/No	M9
	Were the words easy to write?	Likert scale	M10
	When you wrote a word, did the game always understand your handwriting?	Likert scale	M11

(M13) recognition rate (M14), model confidence (M15), and handwriting time per attempt (M16).

The data collected from the experiment was designed to investigate the following research questions:

- **Q1 - Did the game present good usability and engagement for the target audience?** Whether participants were able to understand and interact with the game mechanics intuitively and their level of engagement during interaction. This is measured through M2, M3, M12 and M13.
- **Q2 - Was the game effective in supporting the learning of smart city concepts?** Whether the participants could understand and associate urban elements and planning concepts presented during the game, analyzing M6, M7, M8, M12 and M13.
- **Q3 - Did the game effectively support handwriting practice?** Whether the handwriting activities contributed to writing practice, considering recognition performance and interaction with the input system, measured through M10, M11, M14, M15 and M16.

4. Results

The collected data from questionnaires and gameplay interactions were analyzed quantitatively and organized into three complementary perspectives: game usability analysis, smart city learning analysis, and handwriting practice analysis. Importantly, evidence from these perspectives contributes jointly to answering Q1, Q2 and Q3.

4.1. Usability Analysis (Q1)

The usability analysis was conducted through questionnaires and behavioral metrics extracted from gameplay data. Figure 3 presents the distribution of responses related to fun, perceived ease of use, interaction frequency, and time per level.

The results indicated a positive evaluation of the game experience. M2 showed a strong concentration at the highest values of the scale, suggesting that participants

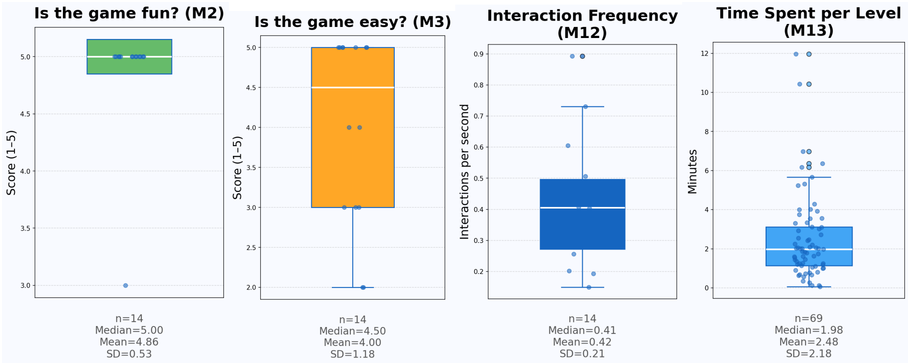

Figure 3. Metric distribution of responses for perceived fun (M2) and ease of use (M3), along with interaction frequency (M12) and time per level (M13).

perceived the activity as engaging. This perception was also reinforced by M12. Participants exhibited a mean of 0.42 interactions per second, indicating continuous and active engagement with the system. This level of interaction suggests that users were not passively observing the game, but consistently interacting with its elements throughout the experience.

The metric M3, although predominantly positive, presented slightly greater variability, indicating that while most users interacted without difficulty, some experienced minor challenges. Considering the heterogeneous profile of the participants, this variation is expected. The time spent per level, measured through M13, shown in Figure 3 provides objective support for Q1. The average time demonstrates that participants were able to complete the levels within a reasonable duration, without significant difficulties interacting with the game system. At the same time, this metric was also relevant to Q2 and Q3. The absence of extremely short durations suggests that participants did not interact superficially, but instead engaged with the tasks, which is necessary for both learning and handwriting practice. Taken together, M12, M2, M3, and M13 supported Q1, indicating that the system provides an accessible and engaging interaction experience.

4.2. Smart City Learning

The effectiveness of the game in supporting learning was evaluated through questionnaire responses related to conceptual understanding. Figure 4 presents the distribution of responses to questions regarding the understanding of smart city planning challenges and general smart city concepts.

The results showed a predominance of positive responses. A total of 85.7% of participants reported that the game helped them understand smart city planning (M8), while 78.6% indicated that it helped them understand smart city concepts more broadly (M7). This perception was reinforced by gameplay behavior, as participants were required to associate urban elements with their functions and apply this knowledge during city construction tasks.

In addition, interaction frequency (M12) and level completion time (M13), presented in Figure 3, demonstrates that participants were able to complete tasks without excessive delays, suggesting that they understood the underlying mechanics and concepts

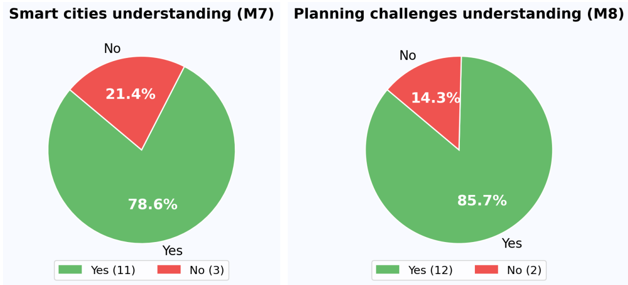

Figure 4. Responses regarding understanding of smart city concepts (M7) and planning challenges (M8).

required for progression and actively interacted to find the optimal urban flow within the levels, providing complementary evidence for Q2. This was particularly relevant in the context of urban planning, where efficient decision-making reflects an understanding of how different elements contribute to city functionality and flow. This pattern supports the interpretation that users were able to internalize and apply smart city concepts during gameplay. Thus, the combination of M7, M8 and M13 provided strong evidence supporting Q2.

4.3. Handwriting Practice

The analysis of handwriting presented the metrics M10, M11, M14, M15, and M16, which collectively summarize accuracy, consistency, and task success across participants. The results of these metrics are presented in Figure 5.

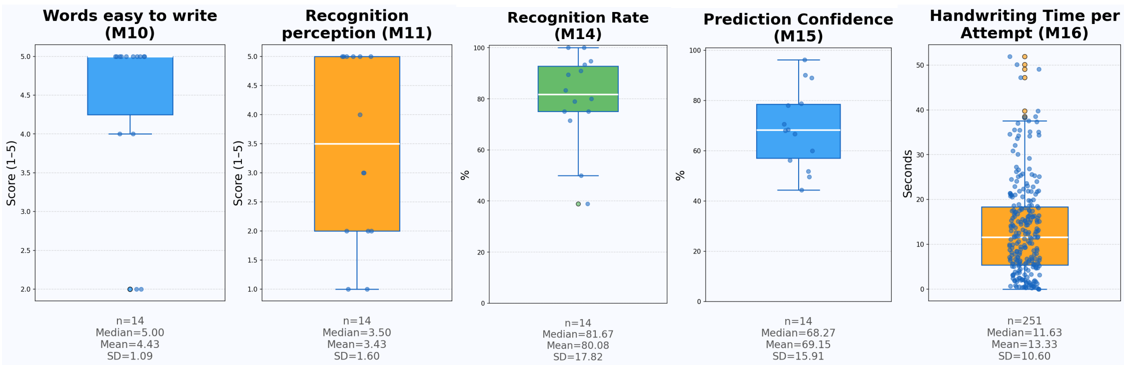

Figure 5. Handwriting evaluation metrics: perceived handwriting ease (M10), recognition perception (M11), recognition rate (M14), prediction confidence (M15), and handwriting time per attempt (M16).

The results indicated that handwriting tasks were generally accessible to participants, as reflected by M10 (mean = 4.43, SD = 1.09, median = 5). This suggests that the interaction design is compatible with the motor skills of the target audience. In contrast, recognition performance presented moderate accuracy with high variability, and perceived recognition (M11) reflected this with a neutral and dispersed assessment (mean = 3.43, SD = 1.60, median = 3.5), which indicated uncertainty in system feedback. The mean recognition rate (M14) was 80.08% (SD = 0.1782), with values ranging from 39.67% to 100%. Similarly, model confidence (M15) averaged 69.15% (SD = 0.1591), that demonstrated uncertainty in predictions. Rather than indicating a limitation solely in the system, this dispersion should be interpreted in light of the characteristics of the target population. Children's handwriting is inherently irregular, particularly across early literacy stages, which contributes to variability in recognition outcomes.

From an interaction perspective, the most relevant finding was sustained engagement. The average drawing time per attempt (M16) was 13.33 seconds (SD = 10.60), with multiple attempts across tasks, that indicated active interaction with the handwriting component despite recognition uncertainty. Level completion time (M13) showed that handwriting tasks were integrated into gameplay rather than bypassed. These results highlighted a distinction between recognition performance and learning support. Although accuracy is moderate and variable, the system promoted repeated handwriting practice. The combination of accessibility, sustained interaction, and repeated attempts suggested conditions conducive to motor practice and skill reinforcement. Considering perceived writing ease (M10), recognition perception (M11), and performance metrics (M14, M15, M16), the findings supported Q3.

The preliminary evaluation indicated high engagement and usability, with most participants understanding the mechanics. However, variability in recognition performance reflected limitations in the CNN model and diverse writing patterns, especially among younger children. Recognition accuracy remains critical to user experience and requires improvement. Despite these results, the study had limitations, including a small sample size and a restricted dataset used to train the recognition model.

5. Conclusion

This research demonstrates the potential of combining serious games, handwriting recognition, and smart city education into a single platform. The approach contributes to innovative educational tools that support both learning and assessment in early education, enabling the analysis of learning and writing patterns and opening avenues for future research on learning difficulties and intervention strategies based on children's gameplay performance.

The results demonstrate that the game provides an interactive environment in which children can learn basic principles of urban planning while practicing handwriting in a contextualized manner. The integration of writing as a core gameplay mechanic proved effective in encouraging participation and strengthening vocabulary associated with smart cities. Additionally, the game data collection enables further analysis of user behavior and handwriting patterns, opening possibilities for educational assessment and early identification of learning difficulties.

Future work should focus on expanding the dataset, improving model robustness, and adjusting the difficulty. More extensive evaluations with larger and more diverse participant groups are also necessary to validate the educational impact of the system.

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