Understanding engagement patterns of game-based learning for children in CatnClever using learning analytics

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***Abstract**. Despite the potential of game-based learning (GBL) for young children, its effectiveness remains under-researched, particularly in preschool education. This study examines engagement data from 8,365 German preschoolers across 60,279 activities within the GBL app CatnClever. Using learning analytics, we aim to assess activity difficulty, learner effort, and performance without relying on formal assessment data. Findings suggest that difficulty aligns well with effort, suggesting optimal challenge levels. Key engagement moments were also identified, potentially informing further interventions. Overall, we stress the potential of learning analytics to deepen our understanding of young learners' interactions in GBL, paving the way for tailored educational strategies.*

Keywords. Game-Based Learning, Learning Analytics, Preschool Education, CatnClever

1 Introduction

It is widely acknowledged that games and game-based learning (GBL) opportunities can spark engaged learning opportunities (Sun et al., 2023). Well-designed games can lead to enjoyable and engaging experiences, in particular for young people and children (Maureen et al., 2022; Plass et al., 2015). Furthermore, games can be fun, interesting, motivating, and playful.

While a lot of literature has focussed on primary and secondary school children (Guan et al., 2024) and adults (Banihashem et al., 2023; Battistella & von Wangenheim, 2016; Gee, 2004; Mahat et al., 2022), there is mixed evidence regarding whether GBL has positive (e.g., knowledge, skills, attitudes) or negative impacts on young children's learning experience (Guan et al., 2024). In particular, there is a paucity of research in how young learners engage in GBL.

As argued in a recent systematic literature review by Guan et al. (2024), play is essential for child development. In this explorative study we aimed to investigate how learners engaged in one specific game-based mobile app called CatnClever that is designed specifically for children aged between 3-6. Using principles of learning analytics and artificial intelligence (Banihashem et al., 2023), we are specifically interested in exploring whether we could use engagement data on children's progress over time in CatnClever to predict learning performance without formal assessment data. As extensive testing of young children might not be appropriate in terms of gameplay, motivation, and data collection (Kucirkova et al., 2024), in this study we sought to explore whether we could estimate the learning performance and activity difficulty of 170 CatnClever activities in four subjects (i.e., mathematics, language, social and emotional learning, and sport) purely from children's engagement data.

2 Background

In a recent systematic literature review of 35 experimental studies of GBL amongst primary school children by Guan et al. (2024) found that 54% of studies reported positive outcomes when using GBL (e.g., academic success, creativity, knowledge, motivation), while 43% reported mixed findings. However, most identified studies used relatively basic descriptives of outcomes rather than actual engagement data, and mostly reported on relatively small samples of learners (< 200 learners).

There is ample consensus on the effectiveness of storytelling as a pedagogical tool, particularly for helping children develop literacy skills in their first language (Koehnecke, 2000), as well as for second language learning (Ellis & Brewster, 2002). But stories can also support learning in subjects like history, science, philosophy and even math (Eades, 2005) and can help learners develop twenty-first century skills like critical thinking (Roche, 2014) and social and emotional learning. Through vivid, dramatic sequences of events, stories create drama, elicit emotion, and convey content in a way that is memorable (Egan, 2005). Stories are powerful, transformative tools that connect even the youngest of learners to the meaning of being humans. As Bishop (1990) noted, stories can be mirrors of our own experiences, windows into other worlds, and sliding doors connecting the two.

Advancements in learning analytics (Banihashem et al., 2023; Chen et al., 2022; Emerson et al., 2020) and artificial intelligence can help to shed light on the complex engagement patterns of learners in GBL. For example, Banihashem et al. (2023, p. 2) argued that “[o]ne promising opportunity in digital GBL is harvesting and analysing learners’ data generated in GBL environments for the purpose of understanding how learning happens in such learning environments to better support the learning process”.

By looking at detailed logfiles and engagement patterns of learners’ progress within a game over time, educators and researchers alike may be able to understand how learning takes place within a unit of a game, across several units or stories, and even across the game over time (Banihashem et al., 2023; Emerson et al., 2020). As GBL environments are often data rich and highly interactive, GBL has the potential to provide a lot of valuable data that could be tracked, analysed, and possibly visualised back to educators, researchers, and even end-users (Kaliisa et al., 2024).

Indeed in their recent systematic literature review of GBL of 20 studies in higher education using learning analytics Banihashem et al. (2023, p. 2) found that all studies used gameplay data, while 30% used player data about the actual gamer, and 20% reported on the game metadata. While these data might be useful for understanding the complexities of game-play and learning, in particular amongst young children, there are obvious concerns in terms and how this could be done in an ethically appropriate manner (Kucirkova et al., 2024).

In this paper we aim to report on how we used learning analytics data to understand the engagement patterns in a GBL environment called CatnClever. CatnClever is a play-based app for children aged 3-6 that supports early language, mathematics, social and emotional learning (SEL), and physical training skills through original, illustrated stories with appealing animal characters and music. Based on the Swiss-German curriculum and the International Baccalaureate Early Years Programme, CatnClever integrates skills (counting and spatial imagination in mathematics; vocabulary and phonological awareness in literacy; empathy and emotional identification in SEL) into playful stories revolving around themes relevant to young children. This story-based learning approach (McQuiggan et al., 2008) is essential in the design of CatnClever. Multimodal features allow learners to actively engage in the stories — in a given activity, they may, for example, count the number of suns (as illustrated in Fig. 1), listen to a word and then tap on its image, and exercise with animal characters working out in real-life landscapes. For example, in Fig. 1 the learners are asked to pinpoint four suns, which exercises their counting and fine motor skills.

CatnClever integrates several strands of research in early childhood learning, namely that play (Scarlett et al., 2004) and storytelling (Casey et al., 2008; Maureen et al., 2022) which are transformative tools for consolidating early literacy, mathematics and other skills. Music (Samsudin et al., 2019) and physical activities also support early learning by giving kids the chance to listen and move their bodies. More recent research has confirmed the value of SEL in the early years (Berlinski et al., 2009; McCormick et al., 2021) to support student well-being and mental health. It also aligns strongly with learning science-based principles of high-quality EdTech products, as app users learn actively, engaged, meaningfully, iteratively, and joyfully (Hirsh-Pasek et al., 2015).

Figure 1. Example of CatnClever mathematics activity

Early years are crucial for children’s basic skill development (Britto et al., 2017). CatnClever's theory of change rests on the power of stories and regular practice: by offering learning experiences through stories that are authentic, interactive, and culturally and linguistically relevant. CatnClever helps young learners acquire foundational skills that will allow them to thrive in school and throughout life. It follows a comprehensive lesson production process which involves various teams such as educators, content writers, software engineers and arts professionals (actors, visual designers, musicians). Currently the app is tailored to English- & German-speaking markets in a European cultural and visual setting.

With a standards-based competency framework for each subject, the app uses adaptive learning to track progress and personalise lessons to the user's pace, strengths and weaknesses, engaging playfully through encouraging direct and indirect feedback (Kapur & Bielaczyc, 2012; Plass & Pawar, 2020). A data dashboard, launched in the period of data collection, allows parents and care-givers to understand their children's progress and engage actively in their learning (Kent et al., 2022).

In order to minimise game-play interference and maximise play and flow, the game lets users play with the tool without a pre-test or knowledge assessment, and uses scaffolding to situate the learner (Cai et al., 2022). Each activity is a learning opportunity for a learner, whereby they will get feedback on how well they have navigated a particular activity. One challenge is to determine the level of difficulty of each activity. Perhaps some activities in one subject might be harder than others, or perhaps some activities take children a bit more time to answer appropriately. In this study we want to explore whether we could estimate activity difficulty of 170 CatnClever activities in four subjects (i.e., mathematics, language, social and emotional learning, and sport) purely from children engagement data.

3 Methods

3.1 Setting and context

At present CatnClever has 160K downloads of the app, and 10K active users per month. In this study we specifically focussed on one group of 8,369 learners from Germany who used the app to complete at least five activities in the period between March and October 2023. We specifically chose this group of learners as these were the largest group of learners of the app in that period. In total these learners completed 63.014 activities on their mobile device (Android or iPhone/iPad), and CatnClever provided them with access to 170 unique activities. As mentioned before, CatnClever uses story-based learning approaches, and while each of these activities is unique, they all do follow a particular story line.

3.2 Activity Difficulty

In order to assess the activity difficulty of the 170 unique activities available to learners in CatnClever in this respective period when the data was extracted, we used two straightforward indicators: (1) the number of ‘Attempts’ and (2) ‘Time to Complete’ each attempt. Given the challenges of conducting detailed assessments with young children, these metrics provide a practical alternative to assessing their knowledge, skills, and competence to complete a particular activity, and can provide the basis for an “activity difficulty” construct and scale that are based on children’s demonstrated abilities rather than external frameworks. 'Attempts' measured how many tries a child needed to complete an activity correctly, reflecting the effort involved. 'Time to complete' tracks how long a child spent on an activity, shedding light on the time commitment required for each respective activity. The activity difficulty score was calculated by aggregating these data across all learners, following these steps:

1. **Data Collection**: Compile 'Attempts' and 'Time to Complete' for each activity from the app’s user data. This step ensured a robust dataset that reflected real-world usage and learning behaviours by participants.
2. **Log Transformation**: To address skewness and manage discrepancies in scale, we apply the logarithmic function log(x+1) to 'Attempts' and 'Time to Complete'. This transformation reduces the impact of outliers, stabilises variance, and improves the normality of the data, ensuring that zero values are handled appropriately. By doing so, it prepares the dataset for more accurate normalisation and analysis, making subsequent calculations reliable and comparable across different activities.
3. **Normalisation**: Apply min-max normalisation to scale the data uniformly. This approach adjusted the data to a common scale, eliminating discrepancies caused by varying ranges in attempts and time, thus ensuring comparability across activities.
4. **Average Calculation**: Determine the difficulty score by averaging the normalised values of attempts and completion time for each activity. This average provided a single, comprehensible metric that encapsulated both the effort and time dimensions of activity difficulty.

In summary, the difficulty of a given activity Aj was computed using the formula:

$$\text{Difficulty}_{A_j} = \frac{\text{Normalized}(\log(\text{Attempts}_{A_j} + 1)) + \text{Normalized}(\log(\text{Completion Time}_{A_j} + 1))}{2}$$

(1)

3.3 Learner effort

Finally, learner effort was computed using the same fundamental metrics as Activity Difficulty—'Attempts' and 'Time to Complete'—but applying them on an individual level rather than aggregating across all users. For each activity completion by a learner, the following process was utilised:

1. **Normalisation of Individual Metrics**: Each learner’s attempts and time to complete were log-transformed and normalised against the activity-specific aggregated ranges, ensuring that the effort measurement was adjusted for the inherent variability in each activity's difficulty.
2. **Effort Calculation**: Learner Effort was then calculated by averaging the normalised attempts and completion time values. This metric reflected the individual effort expended by the learner to complete the activity, distinct from the collective difficulty faced by all learners. For instance, the following formula was used to compute learner effort:

$$\text{Learner Effort}(L_i, A_j) = \frac{\text{Normalized}(\log(\text{Attempts})_{L_i, A_j} + 1)) + \text{Normalized}(\log(\text{Completion Time}_{L_i, A_j} + 1))}{2}$$

(2)

3.4 Learner performance

Learner performance was calculated using the metrics previously discussed for learner effort and activity difficulty. Given the complexity of learning environments and individual differences, our approach to quantifying performance focused on the efficiency with which learners engaged with the activities. Accordingly, learner performance for a specific learner \(L_i\) on a specific activity \(A_j\) was computed using the following formula:

$$\text{Performance}(L_i, A_j) = 1 - (\text{Effort}(L_i, A_j) \times \overline{\text{Difficulty}_{A_j}})$$

(3)

Where:

- Effort (Li, Aj) refers to the learner effort outlined in the previous section (see Section 3.3).

- \overline {Difficulty (Aj)} denotes the average activity difficulty, as detailed in Section 3.2.

This calculation frames performance as inversely related to the product of effort and difficulty, based on the assumption that higher performance is achieved when a learner can complete more challenging activities with less effort. This method allows us to identify potential patterns of learning effectiveness and to tailor further educational content to better suit the evolving needs of learners.

3.5 Data Analysis

The data analysis process comprised several key steps, including data extraction, preprocessing, exploratory data analysis, temporal analysis, and visualisations. Below, we provide more details on how these methods were systematically applied to assess learner engagement and activity difficulty.

Our exploratory data analysis began with initial visualisations to identify outliers in the attempts and completion time metrics, crucial for ensuring data integrity. After outlier removal, we applied normalisation and log transformations to these metrics, enabling uniform comparisons across various activities. This preparation facilitated the calculation of a unified activity difficulty score that accurately reflects the combined demands of effort and time for each activity. In line with recommendations by Alcock et al. (2024) and Kaliisa et al. (2024) we shared the initial insights back with the developers and engineers of CatnClever. Over a period of two months bi-weekly online data sessions were held over Zoom to discuss the initial insights and interpret the findings, and where needed further fine-tune the visualisations and learning analytics approaches. Further investigation involved analysing learner effort across normalised time periods using line plots, which highlighted both general trends and subject-specific variations in effort. This detailed examination helped us understand the dynamics of learner engagement throughout their engagement with the app.

To support this analytical process, we exported our datasets into CSV files for further processing. Subsequent analysis was conducted using Python within Jupyter Notebooks (version 8.20.0), providing an interactive environment for exploratory work. We employed several Python libraries: Pandas (version 2.1.4) for data manipulation, Matplotlib (version 3.8.2) and Seaborn (version 0.13.1) for data visualisation, and NumPy (version 1.26.3) for numerical computations.

4 Results

Our dataset comprised 60,279 entries across 170 unique activities, capturing metrics on learner performance, effort, and activity difficulty. In terms of time to complete, on average children spent 90.25 seconds per activity (range 10.21-1199.18). Obviously some activities required more time for children to complete due to the design of a particular task (e.g., watching a longer video with follow-up activity) relative to other activities. Furthermore, on average 1.16 (range 0-10) attempts were made by the children.

Table 1. Descriptive statistics of learner performance, effort, and activity difficulty (n = 60,729)

	Learner Performance	Learner Effort	Activity Difficulty
Mean	0.86	0.37	0.37
Std Dev	0.06	0.14	0.05
Min	0.42	0.00	0.14
25%	0.83	0.25	0.35
50%	0.85	0.39	0.39
75%	0.91	0.44	0.40
Max	1.00	1.00	0.64

After transforming and normalising the data as described in section 2, the average activity difficulty and learner effort scores both stand at 0.37. This level, on a scale from 0 to 1 – where 0 represents the lowest difficulty and 1 the highest – suggests that the activities are moderately challenging: neither too easy to solve effortlessly, nor too difficult to discourage engagement. The average scores for activity difficulty ranged from 0.14 to 0.64, indicating a broad spectrum of challenges, which can accommodate diverse learner capabilities.

Learner performance showed a high average of 0.86, with a relatively narrow standard deviation of 0.06, pointing to generally high achievement levels among the learners. In essence, a performance score of 0.86 reflects that learners, on average, are able to complete challenging activities while expending relatively low effort. The minimum and maximum performance scores were 0.42 and 1.00, respectively, highlighting a spectrum of outcomes that, while skewed towards high achievement, also includes underperformers (see Fig. 2).

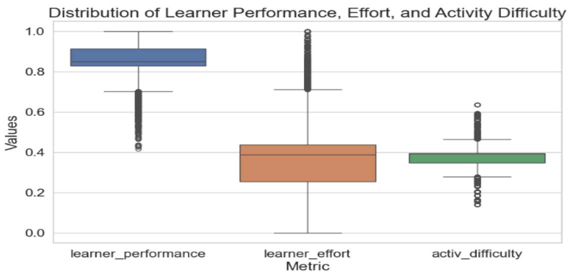

Figure 2. Distribution of performance, effort and difficulty

4.2 Analysis of activity difficulty

As illustrated in Fig. 2, our analysis highlighted significant variability in the difficulty levels across different GBL activities. Fig. 3 illustrates the activities that learners found to be the most challenging as well as those that were relatively easier for learners, followed by a discussion on the average difficulty across different subjects.

Most challenging activities: The activities with the highest difficulty scores primarily comprised puzzles and movement and sport tasks, which demand critical thinking and problem-solving skills. The activity labelled **activity_empathy17_9** emerged as the most difficult, with a difficulty score of 0.64. This score, on a scale from 0 to 1 where 1 represents the highest level of difficulty, indicates that this activity requires significant time and/or attempts relative to other activities in the dataset (see Section 3.2 for details). It was closely followed by **activity_language1** and **activity_training1**, both scoring 0.59. Other notably difficult activities included various puzzles such as **activity_puzzle18_6** and **activity_puzzle12_8**, each with difficulty scores exceeding 0.58. These high scores suggested tasks that likely required higher cognitive engagement and sustained concentration from learners.

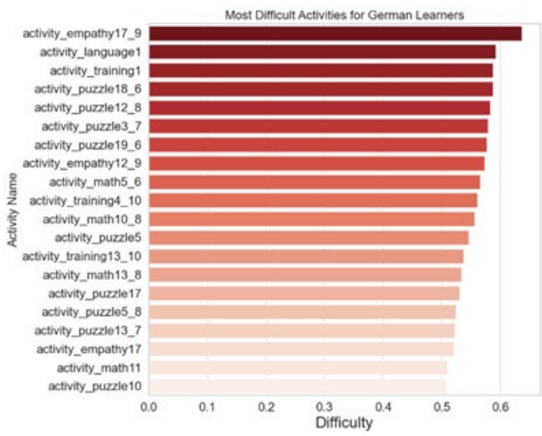

Figure 3. Most challenging activities

Easiest activities: Conversely, as illustrated in Fig. 4 the activities with the lowest difficulty scores were predominantly focused on empathy and language development, suggesting that these might be more accessible or less demanding. The easiest activity identified was activity_empathy3_10, with a difficulty score of only 0.14, significantly lower than the others. This was followed by activities like activity_empathy14 and activity_empathy5, which had difficulty scores of 0.16 and 0.16, respectively. These activities might involve simpler interactions and could be designed to foster basic skills in younger learners or those new to the subject matter.

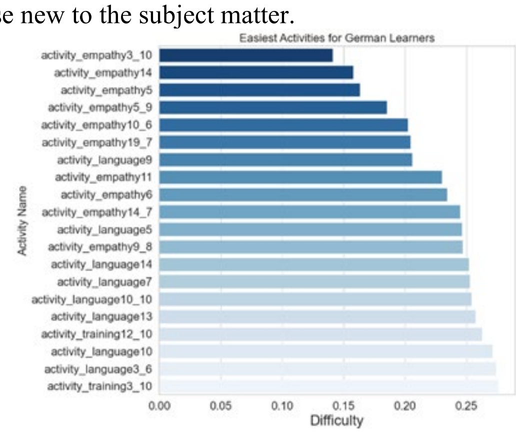

Figure 4. Most easy activities

Difficulty variation by subject: When examining the average difficulty of activities by subject, as illustrated in Fig. 5 mathematics was found to be the most challenging, with an average difficulty score of 0.45. This is indicative of the complex problem-solving and logical reasoning required in mathematics. In contrast, Empathy activities were the easiest on average, with a score of 0.34, possibly reflecting their focus on social and emotional learning rather than problem-solving reasoning. Language and Movement and Sport subjects were moderately challenging, scoring 0.36 and 0.37, respectively.

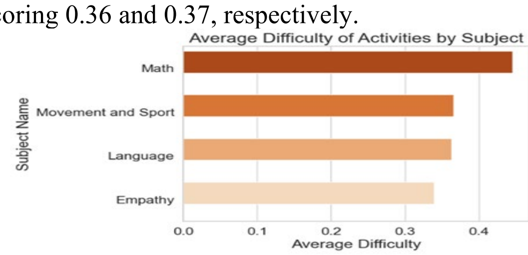

Figure 5. Difficulty by subject

4.3 Analysis of learner engagement

Finally, our analysis of learner engagement over the normalised period from initial to final activity presented a detailed view of changes in effort exerted by learners (See Fig. 6). The normalised time scale, ranging from 0 (the start of the engagement period) to 100 (the end), facilitates a direct comparison of effort levels regardless of the absolute length of each learner's engagement period. As some learners only engaged in a couple of activities, while others completed all 170 tasks this normalised time scale provides an insight into the overall learning effort of learners over time.

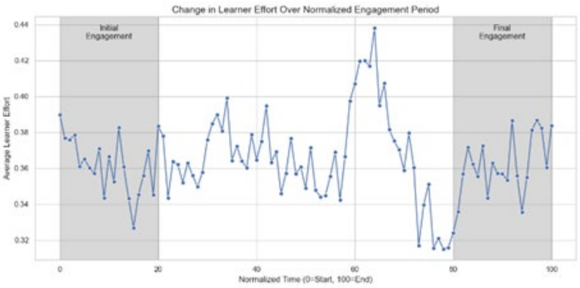

Figure 6. Overall learner effort over time.

At the outset of the engagement period (Normalised Time = 0), the average learner effort was observed at approximately 0.39 on a scale from 0 to 1, where 0 indicates minimal effort and 1 the highest (see Section 3.3). This score reflects moderate initial effort in terms of number of attempts and time needed to complete activities. In addition, this initial effort slightly decreased in the early stages, reaching a lower point around 15% of their engagement time, where it dropped to about 0.34. Interestingly, as learners progressed towards the midpoint of their engagement period, a gradual increase in effort was noticeable, with a peak around 60% of their engagement, recording an effort level above 0.42.

This peak suggests an increase in engagement or a possible response to more challenging or engaging content as the learners approached the middle of their GBL timeline. Following this peak, there was a notable drop in effort, indicating a potential engagement with easier activities. However, as learners neared the end of their engagement period (after instant 80), their effort exhibited slight fluctuations but remained comparatively high, ending with an average effort of about 0.38.

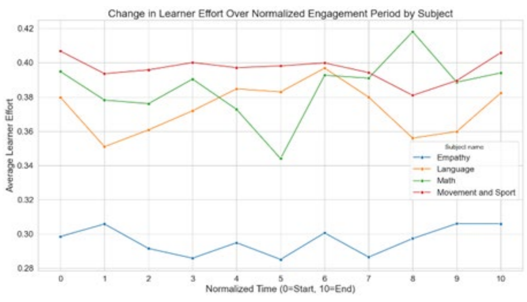

Figure 7. Effort over normalised time by subject

Learner effort over time by subject: Fig. 7 illustrates the variation in learner effort across subjects over normalised time. 'Movement and Sport' consistently shows higher effort, likely due to the physical demands of its activities. mathematics peaked notably at instant 80, suggesting engagement with complex or cumulative reviews. Language effort increased in the middle and late stages, potentially explained by the introduction of advanced topics. In contrast, empathy exhibited consistently lower effort throughout, indicating less cognitive or physical demand in its activities.

5 Discussion

This learning analytics study delved into a largely uncharted territory to predict learning performance without formal assessment data of game-based learning (GBL). As widely discussed in the literature on GBL with young children (Banihashem et al., 2023; Guan et al., 2024; Kucirkova et al., 2024; Maureen et al., 2022; Sun et al., 2023), there are obvious ethical and methodological challenges of frequent and repeated testing of activities by children. Therefore, we explored whether we could estimate activity difficulty, learner effort, and performance across 170 activities in CatnClever using relatively unintrusive engagement data from log data from 8,365 German preschoolers.

Our analysis indicated significant variability in activity difficulty across different GBL activities that are embedded in CatnClever. Mathematics emerged as the most challenging subject overall, followed by language, movement and sport, and empathy. Learner engagement over time exhibited substantial fluctuations, with a notable increase in effort around the midpoint of the engagement period in CatnClever, possibly in response to more challenging content.

The findings of this study underscore the importance of understanding young learners' engagement patterns in GBL environments. The metrics developed during this exploratory study illuminated significant insights into the engagement and success of learners with the educational content provided. The data revealed a strong alignment between the difficulty of activities and the effort learners put in, with both averages mirroring each other. This synchronisation suggests that the activities might be well-tuned to the learners' capabilities, contributing to the high average performance observed. Further investigation could focus on the outliers to better understand the factors affecting lower performance and engagement levels.

The broad range of activity difficulty may reflect a pedagogical strategy designed to reach learners with varied skill levels. Activities categorised under empathy are intentionally less complex, which seeks to consolidate the development of foundational, and contribute to the children's sense of self-efficacy and self-awareness. In contrast, mathematics activities seem to incorporate more intricate puzzles, potentially aimed at fostering early analytical and problem-solving capabilities. This varied difficulty range can contribute to a balanced curriculum that supports both cognitive and emotional growth. Additionally, language and body movement activities presented moderate difficulty levels, potentially promoting language skills and physical coordination, which are essential for holistic development in preschoolers.

The alignment between activity difficulty and learner effort suggests the importance of providing optimal challenge levels to maintain engagement and foster learning. The pattern observed suggests that learner engagement did not remain constant but varied, possibly in response to curriculum complexity, personal adaptation to the learning activities, or external factors affecting learner motivation and capacity to engage. Highlighting specific periods such as the initial, middle, and final phases, we identified where potential interventions or motivational strategies might be most effectively applied to sustain or enhance learner engagement. Moreover, the identification of key engagement moments can inform the design of tailored interventions to enhance learning outcomes. By leveraging learning analytics and artificial intelligence, educators and developers can gain valuable insights into young learners' interactions with GBL apps, enabling the refinement of educational strategies to better meet the needs of preschoolers. However, ethical considerations regarding data collection and analysis in GBL environments warrant careful attention.

6 Limitations and next steps

Obviously a first limitation of our study is that we did not objectively and independently measure the actual activity difficulty of the 170 activities, the inter-related story-based approaches, and the academic performance of the children. At the moment we are working together with pedagogical and disciplinary experts to align whether the identified difficulty levels based upon engagement data correspond with experts' perspectives. A second limitation is that we did not directly ask the children about their lived experiences, and whether (or not) the measured activity difficulty resonated with them. Finally, as we only focussed on a sub-group of German children, future research should explore whether children from other school systems and cultural contexts experienced similar engagement patterns. In future research we aim to explore the relationships between the various stories embedded in CatnClever and user activity/outcomes. Furthermore, we aim to create and validate a tool integrating GenAI and human-led tasks to adapt our learning app CatnClever culturally and linguistically, for children from underserved regions with French and Spanish as language of instruction. Replicable for other languages, the tool will help scale content production and user base, and collect cross-cultural data on early learning. Alliances with the Open University and the Society of Learning Analytics Research will enable product improvement and data accessibility for external researchers.

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