Children's Interaction with Motion-Based Touchless Games: Kinecting Effectiveness and Efficiency

Serena Lee-Cultura
serena.leecultura@ntnu.no
Norwegian University of Science and Technology
Trondheim, Norway

Kshitij Sharma
kshitij.sharma@ntnu.no
Norwegian University of Science and Technology
Trondheim, Norway

Valeria Aloizou
aloizouv@unipi.gr
University of Piraeus
Piraeus, Greece

Symeon Retalis
retal@unipi.gr
University of Piraeus
Piraeus, Greece

Michail Giannakos
michailg@ntnu.no
Norwegian University of Science and Technology
Trondheim, Norway

ABSTRACT

Leveraging movement data to support children's learning is appealing and technically challenging. However, there is limited knowledge about exploiting the complete design potential of bodily interplay in learning games. We conducted an in-the-wild study with 8 children, with special educational needs, playing a language based educational motion-based touchless game. We collected children's interaction data (correctness and reaction time), and data regarding the different design elements (game settings) implemented in 90 game sessions. Our analysis shows that number of items on-screen, selection gestures, and time to select items, impact the effectiveness (correctness) and efficiency (reaction time) of the children. We highlight the value of interaction analytics and quantify the relationship between different game design elements and children's efficiency and effectiveness. Our findings help shape the future of learning research by emphasising the substantial benefits of collecting movement data during children's interaction with learning games.

CCS CONCEPTS

• **Human-centered computing → Gestural input**; **Empirical studies in HCI**; **Empirical studies in interaction design**; **Empirical studies in accessibility**; • **Applied computing → Interactive learning environments**.

KEYWORDS

Motion-Based Games, Educational Games, Child-Computer Interaction, Gesture, Embodied Interaction

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1 INTRODUCTION

Researchers have investigated a rich collection of technologies reflecting different interaction techniques in pursuit of designing movement-based learning games to accommodate the diverse profiles of children with Special Educational Needs (SEN). To further this generative space, a thorough analysis of students' interactions and learning progressions with these games is needed [1, 13]. Previous works leverage on the use of tangible user interfaces [16, 29], multi-touch gestures [4, 27], and interaction with multi-sensory environments [13], and show promise of fostering positive learning experiences both in and outside of traditional classroom settings. Another recent trend in didactic intervention is the use of Motion-Based Touchless Games (MBTG) [6, 8, 24] which depend on sensors to naturally engage the user through "touchless" movement in pursuit of knowledge acquisition, cognitive skill development and advancement of executive functions [24]. Child-centred design and adaptation of game design elements are powerful reoccurring themes of educational Kinect-based games targeting children with SEN [5, 6, 8, 25], as they allow the learning experience to focus exclusively on the strengths or weaknesses of the child. Integration of learning and kinaesthetic analytics help educational support staff and parents, responsible for coordinating learning sessions, to better understand the interplay between customised elements and their effects on learning outcomes [24]. However, despite the potential for rewarding results, little work has been done regarding data-driven investigation into the relationships between adaptable game design elements and the effectiveness and efficiency of learning in the context of MBTG for children with SEN.

Our research investigates the relation between game design elements, and effectiveness (correctness) and efficiency (Reaction Time (RT)), in the context of educational MBTG for children with SEN. We conducted an in-the-wild study in which 8 SEN children played a language development focused MBTG. The SEN covered a collective of unique behavioural and intellectual differences. We collected data pertaining to each session's setup (game setting configuration) and the results of children's interaction with the proposed questions (correctness and RT). We investigated the effect (or combined effects) of the different game settings on children's effectiveness (correctness) and efficiency (RT). By identifying and quantifying these relationships, we provide data-driven design insights for educational MBTG.

2 RELATED WORK

2.1 Addressing Challenges of Designing Educational Games for Children with SEN

Children with SEN exhibit a diverse array of challenges that place them at an academic disadvantage. Many children with SEN are heavily burdened by unfamiliar scenarios [11] and abstract concepts [5], have limited capacity for engaging their imagination [5] and have trouble reaching immersive state [20]. Combined, these impairments complicate the process of designing educational games for children with SEN by requiring additional sensitivity and diligence on behalf of the involved researchers and designers. Moreover, children may not be able to verbalise when they are experiencing difficulty while playing [20], which may lead them to frustration, disengagement and reduced motivation. To keep the "flow" of the game, one needs to adjust game play difficulty [30]. Adjusting game difficulty is typically achieved by balancing the adaptation of learning content with game mechanics to increase learning challenge while maintaining an engaging player experience [21]. Methods for adjusting difficulty by game mechanics rely on adapting various elements; for example, increased speed of challenge and music, and introducing additional objects on screen (i.e. NPCs) [7, 37]. These types of adjustment may be overwhelming to children with SEN due to their "inability to shift attention between input signals" and "over sensitivity" to external stimulus (i.e. noise) [12]. Thus, alternate means of balancing the increased content difficulty with gameplay challenge are needed to address children with SEN, without inducing sensory overload or over stimulus.

Several researchers have put forth a collective of design considerations backed by theoretical and empirical results, purposed to facilitate the development of effective and engaging educational MBTG for children with SEN [6, 8, 14, 20]. Many of these emphasise the importance of adaptability as a key feature of game-based learning interventions targeting such children [6, 8, 24]. Moreover, Kourakli et al. [24] stress three avenues of adaptability purposed to catalyse knowledge acquisition and mitigate the heterogeneous concerns of SEN children; namely relating to learned content, gestural input and game settings. From a different angle, it is also important to aid the mentors in orchestration and facilitation of sessions [20]. Scaffolding provided by mentors while utilising virtual educational environments, particularly during initial sessions, can drive learners toward self-directed game play, which can in turn boost self-autonomy and self-determination of children with SEN [20, 34]. However, it is important that mentors must aspire to attain equilibrium regarding when to support learners with unprompted assistance and when to allow them to struggle through the natural challenges that accompany the learning process. Lastly, researchers highlight the integration of learning and kinaesthetic analytics as a way of obtaining a more holistic representation for a child's overall development [24].

2.2 MBTG with SEN Focus

Prior evidence endorses MBTG for learning [6, 11, 24, 25] in the context of children with SEN and considers such interventions as viable options for classroom integration [24]. However, unstructured play using MBTG does not expedite significant developmental improvements [11]; thus, warranting the need to strategise individually tailored lesson plans [9, 11, 24] according to a given child's required accommodations. Promising results traverse a multitude of domains with success manifested as more fluid problem-solving competencies [10], heightened learning gains [17, 24], short term memory enhancement [31], and elevated executive functions [24]; specifically, increased levels of attention [5, 6, 10, 23] and strengthened emotional responsiveness [15]. Furthermore, a notable subsidiary result evident in numerous studies was strengthened self-confidence [11, 24]. The implications of heightened self-efficacy (found to be correlated to self-confidence [18, 26] and motivation [33]) in children with SEN have the potential to permeate their social, emotional and educational spheres. Heightened self-efficacy has been linked to increased persistence, effort-expenditure, and levels of achievement, as well as heightened interest in activities that were previously deemed unappealing [2, 3]. Research thus far paints a favourable descriptive of motion-based games in special education. However, the state of the art leaves much room for future exploration.

3 MARVY LEARNS: A MOTION-BASED TOUCHLESS LANGUAGE GAME

Marvy Learns is focused on developing a player's language skills, specifically concerning breadth of vocabulary. In this game, the player helps a creature, Marvy, organise a collection of items by placing each into a labelled box. The items are displayed on a card as either an image or a word and are from a mix of different genres such as, fruits, cars, or plants. Defining characteristics of these objects act as the box labels. For example, five items may be: egg, milk, green peas, blueberries and bread; with boxes labels Protein, Grains, Fruits, Dairy, and Vegetables (see Figure 1a). The student must read the box labels, decide which items correspond to each box, then move them accordingly. To answer the question, the student must (1) examine the cards and read the box labels (i.e., see and understand the question), (2) determine which cards correspond to each box (i.e., mentally solve the problem), (3) perform a specified gesture to initiate card selection (i.e., selection mode), (4) maintain the gesture's postural stability for a fixed duration (i.e., the Time to Select (TTS)), and (5) re-locate the selected card to the labelled box. In our example (see Figure 1), the student would be expected to match milk to Dairy, green peas to Vegetables, eggs to Protein, blueberries to Fruit and finally, bread to Grains. Marvy's arms mirror the arms of the player, so arrangement of items takes place as the player moves their arms in physical space. In this way, players learn new words by associating the displayed items with the defined words on the boxes. Marvy Learns also fosters logical and inductive thinking through practice of arranging and classifying objects. Lastly, Marvy Learns offers three adaptable game settings

Figure 1: Marvy Learns requires a child to match an item to a labelled box according to its attributes. *left:* initiate a selection: child assesses item cards labelled: bread, green peas, blueberries, milk, and egg, for sorting into labelled boxes. *centre:* selection process: child chooses the egg card and selection begins. The card is fully selected and movable once it has filled with blue background. *right:* card categorisation: child has moved the egg card into the box labelled Protein.

Table 1: Marvy Learns game settings and the respective values. The high and low levels of the different variables were decided based on the median split of the original values to have a balanced data subsets for adequate comparison

Setting	Value	Description
TTS	Low, High (>1.5 sec)	Time required to hold selection action stable
	Both Hand Delay Mode (BHDM)	BHDM - raise both arms and maintain stable for TTS
	One Hand Delay Mode (OHDM)	OHDM - as above, using arm of dominant hand only
Selection mode	Grab mode (GM)	GM - produce and maintain a grabbing gesture for TTS
# Items	Low (4), High (6)	Number of cards to categorise per question

which instructors utilise to initiate different sessions targeting specific educational outcomes suited to address each child's individual SEN (see Table 1). Once configured, the settings remain fixed for the duration of a session.

4 METHODS

4.0.1 Participants: Our sample was composed of 8 children (6M, 2F) with an average age of 8.7 years (SD = 1.3, min = 7, max = 10 years). Collectively, they completed a total of 90 sessions. All participants were right handed and had SEN. The children had no prior experience with MBTG but quickly became familiar with the natural physical interaction after minimal play.

4.0.2 Context and Procedure: Our exploration is situated in a Greek middle school, where teachers use the Marvy Learns game to assist children to develop their language skills. Marvy Learns was explicitly selected by special educators for each child, after considering their individual SEN, as diagnosed by therapists. School directors collected parental written consent for each child, prior to their participation in this study. The intervention sessions were conducted by two special educators, each of whom received specialised training on the Marvy Learns game, its adaptable settings, and evaluation tools.

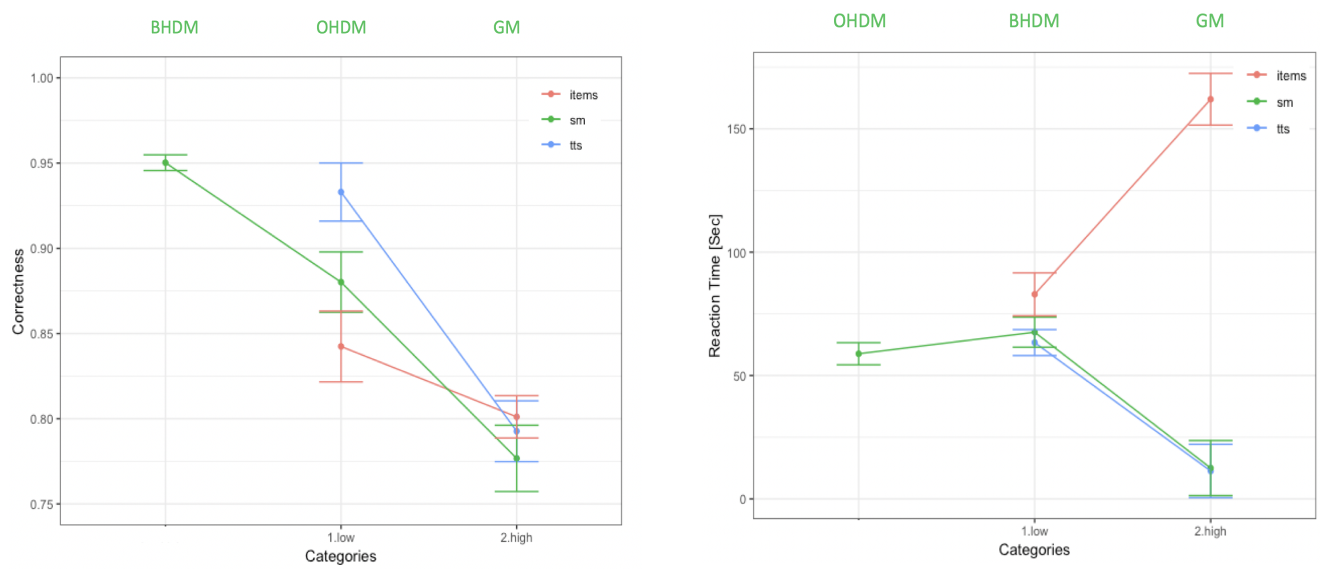
4.0.3 Data Collection: For each session, we recorded the value for all game settings (TTS, selection mode, and number of items) as outlined in Table 1. Additionally, we logged time stamps for the interactions and the correctness of each answer. Children were permitted a practice gameplay session to become acquainted with the game.

4.0.4 Analysis: To investigate the relationship between the three independent variables with the two dependent variables, analysis of co-variance (ANCOVA) was conducted. The factor variables divide the population into groups. Using ANCOVA, the effects of individual factors can be investigated. The independent variables were TTS, selection mode, and number of items. The dependant variables were correctness and RT.

4.0.5 Dependent variables (Correctness and RT):. For time t, correctness is defined as the ratio between the cumulative number of correct answers provided ($correct_t$), and the total number of answers recorded ($total_t$). That is, $COR_t = \frac{correct_t}{total_t}$. The RT begins the moment a child initially sees the problem, to the moment they begin the card selection process (i.e., steps 1-3 as outlined in section 3). Note that the RT and TTS are consecutive actions.

5 RESULTS & DISCUSSION

Initially, we checked for gender bias on the child's correctness and RT. This did not yield any significant results. There was a significant difference between both correctness ($F[1, 88] = 10.42$, $p\text{-value} < 0.05$) and RT ($F[1, 88] = 53.72$, $p\text{-value} < 0.01$) associated with different number of items used during sessions. Specifically, correctness was lower for sessions with high number of items than the correctness for the sessions with low number of items (see Figure 2a). Moreover, when the number of items was high (6 cards), children's RT almost doubled the RT corresponding to a low number of items (4 cards), (see Figure 2b). Essentially, when the number of items was configured low, children answered questions quicker and more correctly. In Marvy Learns, children are presented with all (number of items) of the cards to categorise in the beginning of each question.



(a) Marvy Learns: correctness for different number of items, selection mode and TTS.

(b) Marvy Learns: RT for different number of items, selection mode and TTS.

Figure 2: Single effect of TTS, selection mode, and number of items on correctness and RT for Marvy Learns.

One explanation for the significant difference in RT is that prior to initiating a card selection, children are assessing the breadth of cards to get a complete picture of how they should be assigned to the labelled boxes. Naturally, the duration of time associated with this, increases with the number of items presented, as each additional card requires time so that the children can examine the card, decipher its meaning and characteristics, and mentally match it to one of the labelled boxes. Furthermore, in the sessions with high number of items, the cards are more spatially distributed, so the children must physically move their body a greater distance in order to initiate a card selection. This might also attribute to greater RT associated with high number of items. This movement accumulates across a session, as does the extra cognitive workload associated with categorising additional cards. Thus, the children may be getting tired (mentally and/or physically) in the sessions with high number of items, and consequently, taking longer to categorise remaining cards (increasing RT), and potentially compromising correctness in the process (decreasing correctness).

We observed a significant difference ($F[2,87] = 7.30$, p-value < 0.05) in RT for the GM gesture and the delay-based gestures (OHDM, BHDM), but there was no pairwise statistical difference between delay-based gestures. The GM gesture attributed the lowest (i.e., fastest) RT, followed by OHDM and then BHDM. Additionally, we observe a significant difference in the answer correctness for the different selection modes ($F[2,87] = 14.26$, p-value < 0.05). The correctness for the GM is the lowest, followed by the correctness for the sessions with OHDM and finally, the correctness for the sessions with BHDM. By looking at both correction and RT graphs together, it is apparent that children struggled the most (lowest correctness) when using GM. We observe that the sessions with GM have high RT and low correctness, which is typical behaviour for a trial-and-error strategy. Our working hypothesis for this is the induction of trial-and-error by the GM selection mode, since GM is more natural than the delay-based gestures (OHDM and BHDM). However, further experimentation is required to verify this.

There was also a significant difference between both correctness ($F[1,88] = 91.21$, p-value < 0.01) and RT ($F[1, 88] = 43.11$, p-value < 0.01) associated with high and low TTS. When TTS was set to low, children achieved the most correct answers and yielded higher RT. When the TTS was set to high, RT decreased, and children produced significantly more mistakes (correctness plummeted), see Figure 2a and Figure 2b. This may seem counter intuitive, however, upon further data analysis we observed that as children improved across successive sessions, the educators reduced the TTS for subsequent sessions as a means to continue challenging the children. This is supported by a clear negative rank correlation between the chronological order of sessions and the TTS setting (Spearman Rank Correlation -0.60, $p < .0001$). In essence, this result is due to the nature by which the educators adjusted the game settings across sessions, in response to children's improvement.

5.1 Implications for Design, Theory and Practice

Here, we offer a collection of implications that are motivated by our analysis.

5.1.1 Allow Non-Dominant Hand Leniency in Academic Games. In cases when both hands are involved in the interaction, controlling on-screen objects with the non-dominant hand might amplify mistakes due to reduced motor control. Thus, educational MBTG should offer lenient treatment of non-dominant hand manipulations. As we see in Marvy Learns, BHDM results in lower effectiveness when compared to the remaining gestures (Figure 2a). This is particularly relevant when children are selecting an object or relocating an object to a target destination. Leniency might be realised by widening the selectable area associated with an item, thereby making the process of non-dominant hand selection more forgiving for children. Similar practices could be applied to target destinations by making the corresponding interaction area larger when children are using their non-dominant hands.

5.1.2 Potential Moment for Intervention. A primary outcome from our analyses is the identification of moments when children might benefit greatly from educator intervention. Informing the support staff of these moments, provides the opportunity to scaffold children's learning at precisely the correct time (as difficulties are occurring). Additionally, this might also reduce the cognitive load experienced by the educator, which becomes increasingly important when several children participate in a single session. These moments occur when children are solving problems quickly (low RT) yet incorrectly (low correctness) (e.g., as demonstrated by children's performance using GM). During this time, a system-initiated prompt would be useful to notify the mentor that it is an appropriate time to intervene [35, 36] with 1) emotional and/or motivational support, 2) content specific hints, or 3) to communicate to the child to take their time and answer more mindfully and carefully.

5.1.3 Incorporate Learning Analytics. Learning and kinaesthetic analytics should be used for reflection and design of sessions [32] and embodied learning material. The data available from Marvy Learns are correctness and RT, movement data and game settings. Educators might benefit immensely from using a reflection or guiding tool, such as a carefully designed dashboard or compilation report to evaluate a child's progress across the sessions. These reports can also inform the design of the forthcoming sessions accordingly [32]. Simple visualisations, such as: pie charts illustrating answer correctness, trend lines showing RTs, and well organised presentation of employed games settings and target goals, might equip the educators with the information necessary to determine a child's levels of mastery. They can also highlight which game settings require adaptation in order to catalyse skill development.

5.2 Limitations & Conclusion

We do not claim that our results are generalisable across all SEN populations, and recognise that the extent or variety of SEN might require alternate research designs or produce different results. Notwithstanding, we conducted an in-the-wild study (school settings with special educators) with high-ecological validity data, that produced certain implications. We measured effectiveness (using correctness) and efficiency (using RT); which are valid scales grounded in the literature [24]. However, it is arguable that different scales and techniques such as, sensor data [19], computer vision [22], multi scale measurements [1, 28] could had been used. Though we followed an ecological and accurate research design, we understand that other methodological decisions may play an important role in the results. However, our methodology includes a robust set of data-streams, that are common to contemporary HCI and learning research. We conclude that the selection mode, TTS, and number of items associated with a given task, each impact children's effectiveness and the efficiency during educational MBTG play targeting language development. Our work helps broaden the domain for development of embodied learning research by emphasising the substantial benefits of collecting kinaesthetic and learning data during children's interaction with learning MBTG.

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