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LONG PAPER

Can serious games measure your cognitive profile in adults? An innovative proposal to evaluate and stimulate cognitive skills

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Abstract
The Theory of multiple intelligences suggests that it is necessary to develop new methods to assess and conceptualise the human intellect. It is envisaged that serious games can offer an alternative form of evaluation, as game designers can create gameplay environments that incorporate the different intelligences into clues, puzzles and game challenges, so that players can not only acquire knowledge, social support and self-efficacy, but also easily evaluate their skills and abilities. This study aims to analyse the classificatory precision of cognitive profiles acquired from the use of a serious game based on multiple intelligences as well as examine the agreement between the serious game results and a self-report questionnaire. The sample consisted of 209 participants (22.5% men), aged between 19 and 59 years ($M=22.83$, SD $=6.36$) from secondary to higher education. The results revealed that the serious game presented a different classification capacity compared to the self-report questionnaire. The possibility of identifying different cognitive profiles would have implications for educators and researchers. For educators, it would allow the incorporation of more individualised and inclusive education practices, by adapting teaching methods to each student's learning style. For researchers, it would shed light on the various structures of multiple intelligences in different samples.

Keywords Serious games · Video games · Multiple intelligences theory · Cognitive profiles · Latent profile analysis

1 Introduction

1.1 Serious video games: a powerful cultural and social mechanism

Since their commercial breakthrough in the 1980s, video games have evolved, both in general and serious games in particular, gaining popularity to become one of the main entertainment options for children, young people, and adults, and displacing other, more classic forms of entertainment such as movies and music. According to data from the ESA (Entertainment Software Association) [1], 65% of American adults play serious games, more than other more creative hobbies such as drawing, writing or painting (52%), or playing a musical instrument (32%). The Spanish Video Game Association (AEVI) [2] annual report on the video game industry indicated that the number of video game players in Spain has increased year on year to more than 17 million in 2018 (one million more than the previous year), while frequency of play was estimated to be around 6 h on average per week per player [2]. Moreover, it is important to highlight that the purpose of serious games in the last few years has evolved; video games are no longer used only for personal interest and entertainment, but also for educational objectives [3].

The growth in the games industry is not stopping. It is an industry that is increasing in value every year, and other disciplines have started to emerge around it, such as electronic sports—commonly known as eSports—a phenomenon that

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is garnering increasing social, cultural, economic and scientific interest [4, 5].

1.2 The potential of serious games in non-entertainment contexts

These data reflect the increasing social and cultural impact of serious games on today's society, and justify why thousands of professionals are investigating alternative ways to use serious games—such as encouraging people to learn, increasing motivation in doing an activity, or demonstrating talent in a job selection test. One common example in this area is the serious game America's Army, a military simulation video game whose objective was to promote the US army and serve as a recruitment tool [6]. In addition, gamified applications such as Duolingo, which uses the elements of game design applied to language learning, have resulted in millions of people around the world learning through their mobile devices, breaking time and geographical barriers [7], or playing popular learning-based games such as Minecraft [8], Assassin's Creed [9] and Fortnite [10].

Although some studies have focussed on the negative effects of playing video games—such as addiction, violence and depression [11, 12]—in recent years, researchers have increasingly highlighted the possible benefits of playing video at the cognitive [13], motivational [14], emotional [15], and social level [16] in many different populations.

Unlike more traditional tools, serious games allow information and content to be presented in a wide variety of formats, which increases the chances that relevant information will be addressed [17]. Likewise, serious games also encourage the organisation of information through networks of interconnected concepts, just as our brains process information, which facilitates the rapid activation of content [18]. They also involve some dynamic behavioural factors that are capable of arousing interest, attracting attention, and inducing motivation, such as playful characters, progressive levels of difficulty, competitive situations and rewards [19].

Given the potential and benefits serious games may offer education and psychology, this study aims to analyse the viability of using serious games as tools to determine cognitive profiles. This would then allow teachers, psychologists, researchers and human resource managers to identify skills in a simple, fun and much more easily automated way than is currently available.

Within this context, it is worth noting that the measurement of intelligence and cognitive skills has aroused great interest throughout history because of its ability to predict work performance [20], academic performance [21], health [22] and socioeconomic status [23]. Nowadays, psychometric tests that analyse cognitive abilities are a continuing part of the day-to-day work of education and psychology professionals, who apply these tests to identify and inform interventions for learning difficulties, and to aid personnel selection.

However, despite the constant interest and numerous studies on the potential of using more progressive methods, most of the standardised tests used in the evaluation of cognitive skills remain based on traditional tools, and pencil and paper tests, such as the BADYG batteries [24] and the Wechsler scales [25]. These continue to be successful so, despite the potential of those more progressive methods, it is still difficult for educators, psychologists, and researchers to find tests that enable them to evaluate human skills and cognitive ability in ways that are simpler, more dynamic and more appealing for both evaluator and participant.

Serious games have definite potential as tools for evaluating and identifying cognitive profiles. An evaluation that is conducted by having the participant play a serious game allows evaluation objectives to be incorporated while also entertaining the participant, using an innovative and significant methodology [26]. The gameplay can also be recorded—without bias—and results can be automatically produced from the interactions between the participant and the evaluation tool.

Some success has already been had using so-called brain training video games, with positive results in the identification and improvement of basic cognitive abilities, such as processing speed, working memory, attention and reasoning [27]. However, although “brain-training” games have proven to be valuable, they take a very unitary vision of intelligence, and ignore other, more pluralistic approaches that have emerged during recent decades.

1.3 A tool based on new approaches to human intelligence

New conceptions of intelligence and the mind now exist that are more open and dynamic, and that emphasise a multiplicity of capacities and processes, such as the theories of multiple intelligences [28], emotional intelligence [29] and Sternberg’s Triarchic Theory of Intelligence [30]. Of these pluralistic theories, the theory of multiple intelligences (MI), developed by Howard Gardner and his team in the 1980s [28, 31, 32] is of particular interest. This theory revolutionised the definition of intelligence by considering the concept not as something unique, but as a set of skills, talents or abilities, called intelligences, which were independent from each other and potentially present in all people [32]. According to these ideas, Gardner [31] defined intelligence as "a biopsychological potential to process information that can be activated in a cultural framework to solve problems or create products that have value for a culture" (p. 52).

Gardner [28] initially identified seven intelligences: verbal-linguistic, bodily kinaesthetic, logical-mathematical, musical-rhythmic, visual-spatial, interpersonal and intrapersonal. Later, naturalistic intelligence was incorporated into the theory, establishing a total of eight intelligences. Each individual develops and combines them in different ways, shaping a unique profile and, although we are all born with them, none of us has exactly the same intelligences in quite the same combination [31].

This theory has generated great interest in the fields of psychology and education because it constitutes an interesting model of personal development; knowing a person's profile of intelligences offers the chance to create experiences that will develop strengths, intervene to support the development of weaker areas and activate abilities that may be dormant.

Some tests have evolved to include content that recognises a greater variety of abilities, such as the inclusion of fluid reasoning skills, image concepts, and routine aspects of short-term memory [33] in the latest editions of the Wechsler scales [25]. However, it is still difficult to find instruments that support realistic assessment of performance in different skills, tasks and experiences, while at the same time manage to be intrinsically motivating for the participant, provide feedback on performance, and automatically record responses for further analysis and processing.

Incorporating Gardner's ideas [31] points towards a change that would allow the development of a different, potentially better way to conceptualise the human intellect. Serious games can offer this, as a different method of evaluation, because game designers can create opportunities for players to acquire knowledge, social support and self-efficacy, by incorporating the various intelligences into clues, puzzles and game challenges [26].

1.4 The present study: a serious game to measure cognitive profiles

The new, pluralistic views of the mind, combined with the emergence of new digital tools (capable of measuring skills dynamically and differently), has led to the idea that an evaluation of cognitive profiles utilising serious games is possible.

Therefore, aware of the need for evaluation tools that cover an increasing number of skills and the growing interest in such tools in education and psychology, as well as the cultural impact of video games on today's society, this study aims to analyse the possibilities of using a serious game called Cutie Cuis—based on the theory of multiple intelligences—as a tool for assessing cognitive skills and identifying cognitive profiles in a sample of adults. To that end, Latent Profile Analysis (LPA) will be used to determine the classification accuracy of profiles produced by this serious game through analysis and comparison with profiles obtained using a self-report MI questionnaire.

2 Method

2.1 Participants

A sample of 209 adults from Northern Spain (Principality of Asturias) aged between 19 and 59 years old ($M = 22.83$, SD = 6.36) took part in the study. The participants were selected by convenience sampling. Of the total sample, 22.5% were men, with an average age of 24.04 (SD = 7.83), and the remaining 77.5% were women, with an average age of 22.48 (SD = 6.73). There were no statistically significant differences in the distribution of the genders in the sample ($p = 0.161$). The educational attainment of the sample was as follows: 4 participants (1.9%) had completed compulsory secondary education; 58 (27.8%) had finished post-compulsory secondary education; 20 (9.6%) had done vocational training; 112 (53.6%) studied at university; 7 (3.3%) had done a Master's degree; while 8 (3.8%) did not specify their educational attainment.

2.2 Instruments

Two evaluation instruments were used to gather information about the sample's cognitive profiles: a digital tool based on serious games and a self-report MI questionnaire for adults.

2.2.1 TOI Software, a proposal for evaluating cognitive performance using serious games and multiple intelligences

TOI Software [34] is a digital tool designed based on the ideas of Gardner's Multiple Intelligence Theory [32] to analyse and develop cognitive skills in a playful and interactive way. It uses the serious game as an instrument and is built on two fundamental pillars: an instructional design understood as the planning and design of educational materials, and a conception of intelligence as the ability to solve problems or create valuable product [32].

The TOI software is composed of two mobile phone applications: Boogies Academy, for children from 5 to 9 years old, and Cutie Cuis [*Cui* is Spanish for Guinea Pig], which is designed for adults. In this case, considering the objectives and the age range of the participants, the Cutie Cuis application was used. This application has ten tests in a video game format that explore six of the eight intelligences proposed by Gardner: visual-spatial (visual), logical-mathematical (logical), musical-rhythmic (musical), verbal-linguistic (verbal), naturalistic and bodily kinaesthetic (kinaesthetic).

Table 1 shows a description of the Cutie Cuis games. Each game is pedagogically designed so that participants

Table 1 Description of the games in Çutie Cuis application

Game name	Game mechanic	Worked intelligence	Key skills
Prison Break	Remember the spatial location, colour, and features of guinea pigs to rescue them	Primary: visual-spatial intelligence Secondary: logical-mathematical intelligence	Visual memory Visual tracking Spatial reasoning
Toucan's Jungle	Remember the direction and position of the bamboo canes and calculate the trajectory of the food to feed your guinea pig	Primary: visual-spatial intelligence Secondary: logical-mathematical intelligence	Working memory Visual tracking Spatial reasoning
Dumb Bags	Sort out the guinea pigs in ascending or descending order according to the numeric value and colour of the bags where they are trapped	Primary: logical-mathematical intelligence Secondary: visual-spatial intelligence	Numerical reasoning Visual tracking Planning
Bank a count	Quickly and efficiently perform mathematical calculations, manipulating the numbers mentally	Primary: logical-mathematical intelligence Secondary: visual-spatial intelligence	Mental calculation Working memory Processing velocity
Pop the Word	Pop the balloons in alphabetical order to free the guinea pigs from the evil clown Bob	Primary: verbal-linguistic intelligence Secondary: visual-spatial and logical-mathematical intelligences	Lexical route Visual tracking Planning
Crococui	Coordinate your sight and manual mobility quickly and effectively to prevent the guinea pigs from getting eaten by the Crocs	Primary: bodily kinaesthetic intelligence Secondary: visual-spatial intelligence	Hand–eye coordination Bilateralism Split attention
Cuiboom	Type word codes quickly to deactivate dynamite and prevent guinea pigs from being blasted away	Primary: verbal-linguistic intelligence Secondary: visual-spatial and logical-mathematical intelligences	Lexical route Selective attention Decision making
Punch Pow	Listen, memorise, and repeat the rhythm and tempo of your opponent's hits to beat him	Primary: musical-rhythmic intelligence Secondary: Bodily kinaesthetic intelligence	Rhythm feeling Coordination Sensory
Instazoo	Identify and classify the animals according to their order, diet or fertilisation	Primary: naturalistic intelligence Secondary: visual-spatial and verbal-linguistic intelligences	Categorising Lexical route Processing speed
Merry Cuistmas	Help the guinea pigs discard duplicate objects on the Christmas tree	Primary: visual-spatial intelligence Secondary: logical-mathematical intelligence	Differentiation Visual tracking Decision making

work with one main (primary) intelligence and one or more secondary intelligences; the design of each game considers the key competencies and skills associated with the relevant intelligences. Thanks to the serious game format and interactive ability, the TOI software provides real-time measures of the various performance indicators (correct responses, errors, time spent on the game, precision index and reaction speed). Moreover, a user's score is compared with the recorded performance of other users in each of the games, showing the percentile for each intelligence and a bar graph that allows users to see at a glance their most and least developed intelligences. This gives the users feedback about their intelligence profile, and relevant information on what their percentage of each intelligence means [34].

2.2.2 Self-report questionnaire of multiple intelligences in adults

To provide a comparison for the profiles from the Cutie Cuis serious game, the study also applied a self-report multiple intelligences questionnaire. The questionnaire was produced by the research group, referring to the online Multiple Intelligences Questionnaire by McKenzie [35], the Inventory of Multiple Intelligences by Armstrong [36], and the Self-perception Questionnaire of Multiple Intelligences in Secondary Education Students, produced by the research group on higher Intellectual Abilities at the University of Murcia with good reliability [37].

The questionnaire was made up of 42 items divided into two blocks: *what do you like to do?* (21 items) and *what are you good at?* (21 items). It was evaluated using a 4-point Likert scale (from 1 = Disagree, to 4 = Agree) and encompassed seven intelligences: visual-spatial, logical-mathematical, musical-rhythmic, linguistic-verbal, naturalistic and bodily kinaesthetic. Each of these intelligences was represented by six items, with three in the *what do you like to do?* block and three in the *what are you good at?* block. In this study, the questionnaire (42 items) exhibited good reliability ($\alpha = 0.82$) and the intraclass correlation coefficient (ICC) also indicated good reliability (ICC = 0.794). Moreover, the *what do you like to do?* subscale (21 items) exhibited good reliability ($\alpha = 0.78$) and the *what are you good at?* subscale (21 items) exhibited acceptable reliability ($\alpha = 0.71$).

The percentage of each intelligence making up the multiple intelligences profiles was calculated using the formula: (total score − 6) × 5.55. This equation was derived as follows:

1. As each intelligence has 6 items, and each item has a minimum score of 1 point and a maximum score of 4 points, participants can have a minimum of 6 points and a maximum of 24 points in each intelligence;
2. With these specifications, it is inferred that 6 will be percentile 0 and 24 will be percentile 100. Subtracting 6 from 24 gives us the 50^{th} percentile, in this case 18;
3. The figure 5.55 is the ratio of how often the percentile changes and is obtained by dividing 100/18 = 5.55;
4. Thus, for example, a person scoring 20 points in linguistic intelligence will be placed in the 77.7% percentile (i.e. 20–6 × 5.55 = 77.7%).

In addition to measuring the six intelligences, an Emotional Quotient (EQ) was also evaluated using the self-report application following the model from Goleman [29]. Finally, the digital tool *Google Forms* was used to create and administer the questionnaire due to its capacity to collect results and ease of application.

2.3 Procedure

This study was conducted in accordance with the Declaration of Helsinki and the World Medical Association [38], which establishes the ethical principles of research with humans. Approval was obtained from the ethics committee of the Principality of Asturias (reference: CPMP/ICH/70/19, code: vRTI_Learning). The participants volunteered for the study and anonymity was ensured.

Before administering the serious game, an initial meeting with possible participants was organised, in which they were informed about the main aim of the project, the description of the games contained in the application, the duration of the tasks and the anonymity of the results. This opportunity was also used to answer any questions they may have had about the project. At the end of the meeting, participants who agreed to participate in the project signed their informed consent.

The administration of the Cutie Cuis application and self-report questionnaire took 2 h and participants used their own mobile phones to play the TOI software video games and complete the self-report. Once the project was completed, all participants received a detailed report containing the results from both the serious game and the self-report. Thus, each participant received feedback informing them of their cognitive profiles, as obtained by both assessment tools (serious game and self-report) and based on the Theory of Multiple Intelligences [31].

2.4 Data analysis

To obtain the different cognitive profiles of the participants, a series of latent profile analyses were performed in several phases. First, descriptive statistics corresponding to the serious game and self-report questionnaire were calculated and analysed. Secondly, several Latent Profile Analysis (LPA) was performed [39], both for the data obtained through the questionnaire and for those obtained in the video game, through tablets. The variables used for profile analysis were the multiple intelligences (verbal, logical, visual, kinaesthetic, musical and naturalistic in the case of serious games, and including emotional in the case of self-report). MPlus, version 7.11 [40] was used to determine the best fit to the data from a finite set of models, adding successive latent classes to the target model. Third, the model with the optimal number of classes was determined by considering the Akaike information criterion (AIC), the Schwarz Bayesian information criterion (BIC), the sample size adjusted BIC (SSA-BIC), the formal test of the adjusted maximum likelihood ratio by Lo, Mendell and Rubin [41] (LMRT), and the sample size for each subgroup. The p value associated with the LMRT indicates whether the solution with more or fewer classes is the best fit to the data. The AIC, BIC and SSA-BIC indices are descriptive, with lower values indicating better model fit. Also, classes containing less than 5% of the sample are considered spurious, a condition indicative of excessive profiling [42], although it is possible that a class with less than 5% of the subjects makes theoretical sense. Finally, once the best-fitting model was selected, to determine the ranking accuracy of the selected model, the ex post probabilities and the entropy statistic were taken into account (entropy ranges from zero to one, with values closer to one indicating higher ranking accuracy).

3 Results

Table 2 shows the descriptive statistics and Pearson's correlations between the multiple intelligences for the two applications (video game and self-report). Emotional intelligence was evaluated in the self-report application, in addition to the six intelligences evaluated in both applications. The correlation matrix shows that almost all the correlations were statistically significant.

According to the criteria indicated by George and Mallery [43], the asymmetry and kurtosis data indicate that the variables followed a normal distribution since they were between the values − 2 and + 2. The results of the correlations between the MI evaluated in the video game application showed the same pattern, with statistically significant associations between all components and acceptable values of asymmetry and kurtosis.

Table 2 Descriptive statistics and correlations between the multiple intelligences measured using a Serious Game and a Self-Report ($N = 209$)

Variables	1	2	3	4	5	6	7
Serious game							
1. LOGICAL	–						
2. VERBAL	0.476**	–					
3. KINAESTHETIC	0.437**	0.386**	–				
4. MUSICAL	0.462**	0.458**	0.365**	–			
5. NATURALISTIC	0.323**	0.340**	0.431**	0.491**	–		
6. VISUAL	0.236**	0.216**	0.638**	0.212**	0.558**	–	
M	54.47	55.46	53.56	51.82	58.37	54.18	
SD	15.69	14.14	13.25	14.86	15.90	15.48	
Asymmetry	−0.346	−0.412	−0.168	0.092	−0.598	−0.042	
Kurtosis	−0.092	0.030	0.190	0.576	0.889	0.116	
Variables	1	2	3	4	5	6	7
Self-report							
1. VERBAL	–						
2. LOGICAL	0.503**	–					
3. VISUAL	0.296**	0.100	–				
4. KINAESTHETIC	0.237**	0.143*	0.570**	–			
5. MUSICAL	0.237**	−0.055	0.395**	0.242**	–		
6. NATURALISTIC	0.459**	0.341**	0.380**	0.416**	0.280**	–	
7. EMOTIONAL	0.452**	.280**	.323**	.387**	0.258**	0.422**	–
M	53.16	51.62	61.53	63.00	53.96	59.78	73.32
SD	14.37	13.65	16.33	14.39	19.25	14.85	13.12
Asymmetry	−0.213	0.079	−0.206	−0.681	0.157	−0.145	−0.367
Kurtosis	0.578	0.348	0.138	1.122	−0.122	0.415	−0.029

Scale to measure multiple intelligences self-report (minimum: 1; maximum: 4)

*$p < 0.05$; **$p < 0.01$

3.1 Profile identification based on multiple intelligences

Several latent profile models were analysed for each of the applications: serious game (two- to five-class models) and self-report (two- to seven-class models). All models were specified assuming that variances could differ between indicators within each group, but they were constrained to be equal between groups. Also, independence between indicators, both within and between groups, was imposed as a constraint.

Table 3 shows the results of the model fit for the two applications. For both applications, the process was stopped when indicated by some of the model comparison indices. Specifically, model fit was stopped at five- (serious game) and seven- (self-report) classes, since the BIC values for the five- and seven-class models were higher than for the respective four or six class models. Nonetheless, in both cases, according to the values of the SRML statistician, the five- and seven-class models were not statistically better than the four- and six-class models. In addition, the value of entropy was high in both of these models. Therefore, taking into account the heuristic value of parsimony [44], the four- and six-class models were chosen as the most suitable for the serious game and self-reporting applications, respectively.

3.2 Analysis of the classification accuracy of the multiple intelligence profile models

The classification accuracy of the two models (serious game = four classes, self-report = six classes) was analysed based on the value of entropy and the probability coefficients a posteriori. Both models exhibited good values for entropy (serious game four classes = 0.85; self-report six classes = 0.84). Table 4 shows the classification accuracy of the four-class (serious game) and six-class (self-report) models, as well as the number of subjects in each class, both in absolute (N) and relative (%) terms. Table 4 shows the posteriori probability coefficient of each participant belonging to a given class. The coefficients associated with the groups to which the participants have been assigned are shown in the main diagonal of the table for both models.

Table 3 Latent profile model fit information

Variables	Latent Profile Model					
	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes	7 Classes
Serious game						
AIC	3363.683	3287.211	3255.934	3238.057		
BIC	3427.188	3374.112	3366.231	3371.750		
SSA-BIC	3366.986	3291.730	3261.670	3245.009		
Entropy	0.721	0.798	0.849	0.857		
$n \leq 5\%$	0	0	1	1		
LMRT	221.088*	88.116*	44.098	31.047		
Self-Report						
AIC	3998.400	3927.095	3893.900	3857.167	3840.854	3827.456
BIC	4071.931	4027.366	4020.909	4010.914	4021.340	4034.680
SSA-BIC	4002.224	3932.310	3900.505	3865.162	3850.240	3838.231
Entropy	0.757	0.817	0.801	0.810	0.838	0.860
$n \leq 5\%$	0	0	0	1	1	2
LMRT	186.044	85.308	48.070	51.528	31.574	28.727

AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; SSA-BIC, BIC Sample-Size adjusted Bayesian Information Criterion; LMRT, Lo–Mendell–Rubin Test

$*p<0.01$; $**p<0.01$; $**p<0.001$

Table 4 Characterisation of latent profiles and accuracy of the participant classification in each profile

	Profiles of multiple intelligences							
Modality	1	2	3	4	5	6	N	%
Serious game								
1. Low[a]	**0.922**	0.064	0.001	0.013			29	13.9
2. Moderate	0.033	**0.918**	0.047	0.002			122	58.3
3. High	0.000	0.074	**0.926**	0.000			50	23.9
4. Very Low[b]	0.079	0.056	0.000	**0.865**			8	3.9
Self-Report								
1. Low/High[c]	**0.833**	0.114	0.000	0.053	0.000	0.001	16	7.6
2. Moderate	0.014	**0.896**	0.000	0.035	0.020	0.035	108	51.7
3. Very Low	0.000	0.000	**0.966**	0.034	0.000	0.000	8	3.8
4. Low	0.013	0.087	0.002	**0.852**	0.046	0.000	32	15.3
5. High/Low[d]	0.000	0.109	0.000	0.041	**0.850**	0.000	15	7.2
6. High	0.001	0.064	0.000	0.000	0.000	**0.935**	30	14.4

[a]Low Intelligence Profile, mainly in Logical and Verbal Intelligences

[b]Very Low Intelligence Profile, mainly with very low scores in Visual, Naturalistic and Kinaesthetic intelligences

[c]Combined Intelligence Profile (Low scores: Logical, Verbal and Emotional intelligences; High scores: Visual and Kinaesthetic intelligences)

[d]Combined Intelligence Profile (High scores: Logical and Verbal intelligences; Low scores: Visual, Kinaesthetic and Music intelligences)

The coefficients of the two diagonals (in bold) were all around 0.9, which is indicative of very good classification accuracy and, by extension, a good level of confidence that the participants belong to the assigned profile.

3.3 Descriptions of the multiple intelligences profiles

Table 5 shows the average scores of the participants

Table 5 Description of multiple intelligences profiles obtained through a serious game and a self-report

Profiles of multiple intelligences	Serious game		Self-report	
	Z scores	Raw scores	Z scores	Raw scores
Profile 1				
Logical	− 1.483	29.002	− 1.072	35.381
Verbal	− 1.234	37.725	− 1.231	37.115
Kinaesthetic	− 0.785	43.375	0.773	69.721
Musical	− 1.017	35.744	− 0.228	75.618
Naturalistic	− 0.594	48.186	− 0.443	49.950
Visual	− 0.296	50.325	0.543	52.725
Emotional	–	–	− 1.025	58.968
Profile 2				
Logical	0.149	56.919	0.057	55.608
Verbal	0.077	56.565	0.135	52.619
Kinaesthetic	− 0.172	51.273	0.075	63.632
Musical	0.056	52.478	0.225	63.646
Naturalistic	− 0.124	56.426	0.124	58.909
Visual	− 0.285	49.753	0.118	61.484
Emotional	–	–	0.161	75.661
Profile 3				
Logical	0.656	64.954	− 1.495	27.056
Verbal	0.622	64.067	− 1.813	31.218
Kinaesthetic	1.076	68.286	− 2.320	34.687
Musical	0.653	62.257	− 1.096	29.831
Naturalistic	0.966	74.744	− 1.782	32.606
Visual	1.121	72.367	− 1.652	33.300
Emotional	–	–	− 1.841	49.256
Profile 4				
Logical	− 0.690	44.103	− 0.523	41.625
Verbal	− 0.353	49.322	− 0.738	44.226
Kinaesthetic	− 1.464	33.452	− 0.657	46.307
Musical	− 1.151	34.992	− 0.432	53.245
Naturalistic	− 2.268	22.820	− 0.760	43.532
Visual	− 2.044	22.236	− 0.880	49.082
Emotional	–	–	− 0.574	65.732
Profile 5				
Logical			1.198	62.530
Verbal			0.610	69.190
Kinaesthetic			− 0.685	39.590
Musical			− 1.125	53.650
Naturalistic			0.017	31.080
Visual			− 1.220	60.680
Emotional			− 0.034	73.630
Profile 6				
Logical			0.613	68.450
Verbal			1.035	60.310
Kinaesthetic			0.978	83.990
Musical			0.662	77.885
Naturalistic			1.015	66.600
Visual			1.290	75.480
Emotional			1.020	86.950

Table 5 (continued)

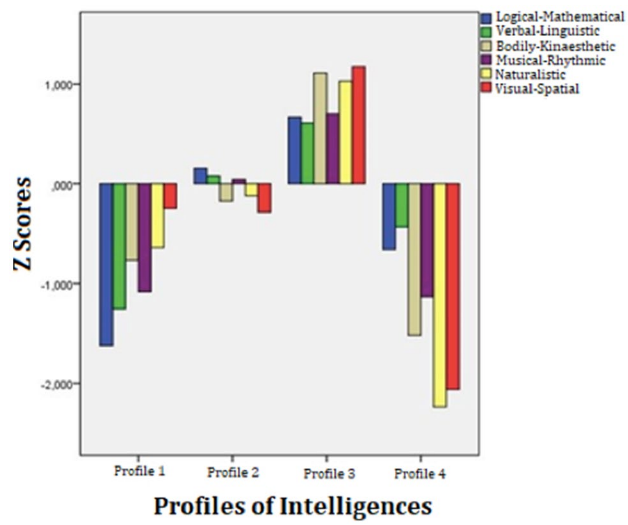

Fig. 1 Graphical representation of the profiles of multiple intelligences (serious game)

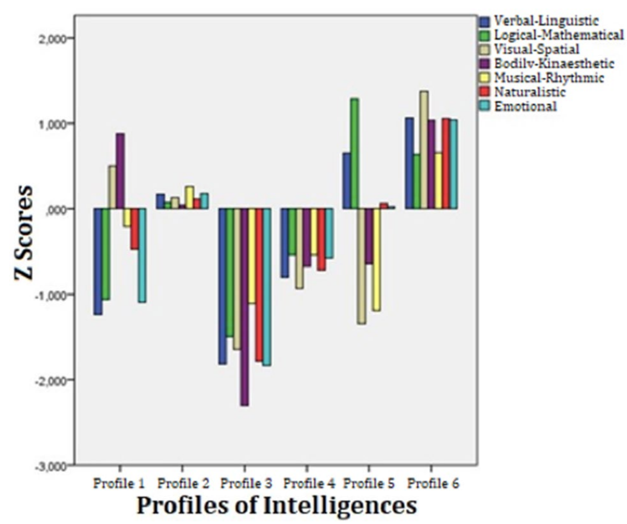

Fig. 2 Graphical representation of the profiles of multiple intelligences (self-report)

belonging to the multiple-intelligence profiles resulting from the serious game four class model and the self-report six class model (z scores and raw scores). Figures 1 and 2 show graphical representations of these profiles.

The best-fitting model for the profiles for the serious game application (Fig. 1) distinguished four latent classes.

The profile with most member was a moderate level multiple intelligence profile (Profile 2 = 58.3%). There was also a high level multiple intelligence profile (Profile 3 = 23.9%), a group of participants with a low level multiple intelligence profile (Profile 1 = 13.9%), and another small group with a very low level multiple intelligence profile (Profile 4 = 3.9%).

The best-fitting model for the self-report application (including EQ) had six classes or highly differentiated profiles (Fig. 2). The most populous (51.7%) was a moderate level multiple intelligence profile (Profile 2). That was followed by a low level multiple intelligence profile (Profile 4 = 15.3%) and a high level multiple intelligence profile (Profile 6 = 14.4%), with musical and logical intelligences standing out in this profile for their comparatively low levels (Fig. 2). There was also a small group of participants with very low profiles in multiple intelligences (Profile 3 = 3.8%), mainly in the kinaesthetic, naturalist, emotional and verbal intelligences. Finally, there were two similar-sized groups with two different profiles, resulting from the combination of different levels of multiple intelligences. Specifically, one profile had low verbal, logical and emotional intelligences, but high visual and kinaesthetic intelligences (Profile 1 = 7.6%), while the other profile had high levels of logical and verbal intelligences, but low levels of visual, kinaesthetic and musical intelligences (Profile 5 = 7.2%).

As Fig. 1 (serious game) shows, Profiles 1 and 4 (Low and Very Low profiles, respectively) indicate the existence of two groups that are very clearly differentiated in terms of which intelligences the participants score low on. Participants in the Low profile group (Profile 1) had notably lower scores in logical, verbal and musical intelligences—areas traditionally related to formal education and academia, while participants in the Very Low profile group (Profile 4) scored lower in kinaesthetic, naturalistic and visual intelligences—areas generally related to informal knowledge or curiosity. This pattern suggests that even when considering participants with low cognitive profiles in MI, there are qualitative differences among them. This means it is important to identify such profiles. With regard to Profiles 2 and 3 (Moderate and High profiles, respectively), it is also worth noting that the kinaesthetic, naturalistic and visual intelligences show the opposite pattern (Moderate but below average in Profile 2, and Very High in Profile 3), meaning that there are again differences between different sub-groups of intelligences.

Figure 2 shows the six profiles obtained from the self-report group; these profiles exhibit more complex qualitative differences. Specifically, Profile 3 shows very low levels and Profile 6 shows very high levels in all of the intelligences evaluated. The lowest scores in Profile 3 are verbal and kinaesthetic intelligences, while in Profile 6, both of those, along with visual intelligence, are at their highest levels. The pattern in Profile 3 (Very Low level) is also found in Profile 4 (Low level), although to a lesser degree (with significantly lower z-scores for Profile 3). In addition, Profiles 1 and 5 (Low/High and High/Low intelligence combinations, respectively) differed substantially between each other. Profile 1 shows high levels in visual and kinaesthetic intelligences and low levels in the others, while Profile 5 shows high levels in verbal and logical intelligences but very low levels in visual and kinaesthetic intelligences and in musical intelligence. Again, visual and kinaesthetic intelligences tend to exhibit similar levels, as do verbal and logical intelligences; sometimes these groups are both high or both low, but in some cases one group is low while the other is high. Additionally, musical intelligence tends to group with the naturalistic and emotional intelligences, with the only exception in Profile 5. Finally, Profile 2 (Moderate level) shows average levels in all of the seven intelligences evaluated.

4 Discussion

The present study aimed to analyse the possibility of using a video game based on MI (Cutie Cuis) to evaluate cognitive skills in adults, and to correlate these results with results from a self-report questionnaire. To that end, Latent Profile Analyses were performed. The results showed that the Cutie Cui application demonstrated a different capacity for identifying different profiles of intelligences than the self-report questionnaire, since the serious games produced four profiles of intelligences while the self-report identified six. These results are consistent with Gardner's Theory [31], which stated that standardised tests can only measure a small fraction of the full spectrum of an individual's capacities or intelligences. Moreover, the evaluation of intelligences using this type of serious game allows a more realistic assessment to be made than assessment using traditional tests—whose aim is to obtain a general IQ—as it provides multiple tasks and experiences associated with each intelligence. This technology also makes it easier to access larger, more diverse samples than traditional testing allows and record a large amount of data in real time.

Analysis of the self-report data revealed two clearly differentiated profiles of intelligences: Profile 1 and Profile 5 (Fig. 2). Members of Profile 1 have high levels in the visual-spatial and bodily kinaesthetic intelligences, and low levels in the other intelligences, while members of Profile 5 show high levels in the verbal-linguistic and logical-mathematical intelligences but very low levels in the visual-spatial and bodily kinaesthetic intelligences. People with Profile 1 are often overlooked and ignored in schools, as these abilities are not usually measured in traditional standardised tests of intelligence. In contrast, those with Profile 5 are more likely to be identified, because both logical-mathematical and verbal-linguistic abilities are closely related to the academic curriculum and standardised IQ tests generally focus on these abilities more than the other intelligences. These findings partially support the idea that there is more than one type of intelligence and that they are independent of each other [28, 31, 32]. The possible distinction between "formal" or "academic" and "informal" intelligences can also be seen in the profiles resulting from the video game (Fig. 1), where logical-mathematical, verbal-linguistic, and musical-rhythmic intelligences are present in high levels in Profile 1, whereas bodily kinaesthetic, naturalistic, and visual-spatial intelligences are highlighted in Profile 4.

Despite the Cutie Cuis application being designed and developed according to Gardner's MI Theory, with consideration of key aspects such as designing motivating material, neutrality, the presence of a natural environment, and the provision of real-time feedback [34], it is still very difficult to achieve unequivocal classification and structure for the different cognitive profiles. In this regard, those who had high scores in one task (which measured a specific type of intelligence) tended to also have high scores in the remaining tasks which measured other intelligences. This pattern is clear in the results from the video game application (Profile 2) and in the self-report application results (Profiles 2, 3, 4 and 6). It goes against ideas proposed by Armstrong [36] about MI Theory, who stated that, in general terms, people present some highly developed abilities and other moderately developed abilities, while the remaining abilities could be relatively underdeveloped.

However, while taking into account the fact that it seems difficult to find an assessment tool that is completely compliant with the ideals of the Theory of Multiple Intelligences, the present study still adds support to some of the ideas from Armstrong's study [36]. Specifically, the idea that in order to obtain a reliable assessment of MI, assessment data (collected from the playing of a serious game) needs to be complemented with data from other types of instruments based on observation, such as self-reports. More particularly, the present study showed that the both instruments used yielded different, important information for understanding each participant's cognitive profile.

In this regard, the type of analysis used (LPA) could help to add some evidence in terms of the structure and contextualisation of MI. Many authors have attempted to obtain the structure of MI by collecting data using questionnaires and other means and applying factor analysis [45, 46]. However, there is no agreement in these studies on the number of dimensions obtained. Attempting to identify profiles rather than a fixed factor structure may have important practical implications for educators and researchers.

When it comes to student learning styles, the possibility of identifying different profiles of intelligence could have several educational implications. One of these is the provision of more individualised, inclusive education than is currently generally the norm, by adapting teaching methods to fit each student's learning styles. Considering the traditional VARK classification of learning styles (i.e. Visual, Auditory, Read-written and Kinaesthetic) [47], it might be possible to enhance the learning process in people who present Profiles 1 or 5 (video game), for instance, by adapting the teaching–learning process and the content to their preferred style. Specifically, students who present Profile 1 may feel more comfortable learning with a visual and kinaesthetic learning style, so that information presented in video or other visual formats, and scenarios where students can learn from their own experiences, may bring about more effective learning. On the other hand, students who present Profile 5 might feel more comfortable learning with reading/writing or auditory learning styles, where the content is presented as words (either reading, writing or using the language orally).

Within this context, serious games may be considered suitable tools for identifying cognitive profiles. In fact, previous research [48] has shown a strong relationship between the results obtained in IQ tests and performance demonstrated using serious games.

5 Conclusions

Using applications like Cutie Cuis offers many benefits in education. In particular, these types of applications facilitate more personalised, inclusive education than is currently typical by taking into account individual skills and abilities—both strengths and weaknesses—reinforcing strengths while also developing weaker areas through those stronger skills.

In addition, a psychological intervention program should be designed considering the implementation of these types of tools, establishing the number of work sessions and the types of skills needing to be trained in each session. Implementing these applications would also allow pre-test and post-test differences to be measured to assess the impact of the intervention. There are also notable implications in the field of learning disabilities intervention, based on the principles of cognitive stimulation and brain neuroplasticity [49]. More specifically, considering the results from studies by Del Moral et al. [27, 50, 51] and García-Redondo et al. [13], there have been improvements in cognitive skills, with significant improvements in attentional levels achieved after applying an intervention program with games in the Cutie Cuis app [13].

Finally, it is important to highlight some of the present study's limitations. Firstly, the sample size; it would be prudent to increase the sample size and determine whether future studies with more representative samples substantiate the patterns found in the present study. It is worth noting that in the current study, two of the profiles (Profile 3 from the self-report assessment and Profile 4 from the video game assessment) represented less than 5% of the participants. Although from a theoretical viewpoint both profiles make sense, a broader sample would be necessary to confirm their existence. Secondly, it would be helpful to gather feedback from teachers and the educational community and make adjustments to improve the TOI software where applicable. Lastly, further studies that consider variables such as gender, or professional and educational characteristics of the adult sample would add further external evidence regarding the validity of the profiles obtained.

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Availability of data and materials The datasets used and/or analysed in the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there are no conflicts of interest.

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