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Can digital games help us identify our skills to manage abstractions?

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Abstract In this work we present our progress in the field of Intelligent User Profiling. Our objective is to build a user profile that captures users' skills rather than classical users' interests. Thus, we propose a novel approach to learn users' skills by observing their behavior during a very common activity: playing games. Specifically, we automatically identify users' skills to manage abstractions by using digital games. Abstraction skills identification is important because it is related to several behavioral tendencies such as career preferences, aptitudes, and learning styles. Traditional skills identification is based on questionnaires whose application implies many complications, including non-intentional influences in the way questions are formulated, difficulty to motivate people to fill them out, and lack of awareness of the consequences or future uses of questionnaires. To address these limitations, we built a user profile that collects users' actions when playing digital games. Then, we built and trained a Hierarchical Naive Bayes network to infer users' skills to manage abstractions. The experiments carried out show that digital games can help us to identify abstraction skills with a promising accuracy.

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1 Introduction

People have different skills to manage abstractions. Those who grasp abstractions easily are able to understand concepts, principles and theories almost without effort [27]. In contrast, people that learn by example prefer to understand abstractions by solving concrete problems that allow them to exercise abstract principles [13]. Knowing a person's skills to manage abstractions is important because it has been shown to be correlated with career preferences and aptitudes, management styles, learning styles, and various behavioral tendencies [13, 32].

User profiles are a distinguishing feature of computer systems that model user information such as user's skills, knowledge, interests and goals. Basically, a user profile is a representation of information about an individual user that is essential for the system. In this way, user profiling allows computer systems to infer unobservable information about users from observable information about them, such as their actions or utterances [34].

In this article, we propose an approach to build a user profile to identify a person's abstraction skills by using digital games. Digital games are considered a successful tool for exercising skills such as problem solving, co-operation, negotiation and peer tutoring, among others. It has been proven that digital games possess several advantages over traditional skills questionnaires, including the creation of compelling experiences that mimic real

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situations, the capacity to capture players' attention, and the ability to make training meaningful, fun and intellectually challenging, to name a few [36].

To identify abstractions skills, we base our research on the perception dimension of the Felder - Silverman model [13], also known as Felder's model. This model describes preferences for learning according to four dimensions: perception, processing, input, and understanding. Particularly, Felder's perception dimension describes how people tend to perceive the world according to their skills to manage abstractions. Thus, throughout this paper we use the terms *perception dimension* and *abstraction skills* interchangeably. In this context, Felder's perception dimension states that *intuitive* people are skilled at understanding principles and theories easily; *sensitive* people like data, facts and experimentation, favoring concrete content over abstraction; and *neutral* people are well balanced on the dimension exhibiting standard skills to manage abstractions.

Our approach to identify abstraction skills consists of building a user profile that contains players' actions registered during playing (see Fig. 1). The user profile is used to classify a person as *intuitive, sensitive,* or *neutral* by using a Hierarchical Naive Bayes (HNB) classifier [40]. The HNB classifier models several features related to the perception dimension enumerated in Felder's model. We categorized several digital games that exercise different skills related to the perception dimension. Thus, we implemented 13 digital games to collect information that describe a person's skills to manage abstractions. We evaluated our approach with 147 Computer Science students. Experimental results show that digital games helped us to identify students' abstraction skills with an accuracy of 81 %.

2 Felder's model

Felder's model specifies a small number of dimensions that collectively provide a good basis for designing effective instruction [11]. Felder's model is one of the most referenced frameworks in the literature for several reasons. First, the model provides a free, simple and heavily tested 44-item questionnaire called ILS (Index of Learning Styles) that allows researchers to easily quantify people's learning preferences [12]. Second, Felder's model considers learning preferences not as fixed traits but as differential inclinations for learning, which means that learning preferences are relatively stable and change over long periods of time. Lastly, although Felder's model was successfully used in many research areas [22, 35, 39], it was especially designed for engineering students, and thus it is suitable for our research context.

In this section, we describe each dimension of Felder's model and the ILS questionnaire proposed by Felder and Soloman [14] to quantify people's learning preferences. Finally, we focus on Felder's perception dimension and describe its features.

2.1 Felder's model dimensions

Felder describes how people perceive, process, receive and understand information based on four dimensions: perception, processing, input, and understanding, respectively [13]. The perception dimension describes how people tend to perceive the world according to their skills to manage abstractions. This dimension defines two learning styles: *sensitive* and *intuitive*. Sensing involves observing, and gathering data through the senses. In contrast, intuition involves indirect perception by way of the unconscious

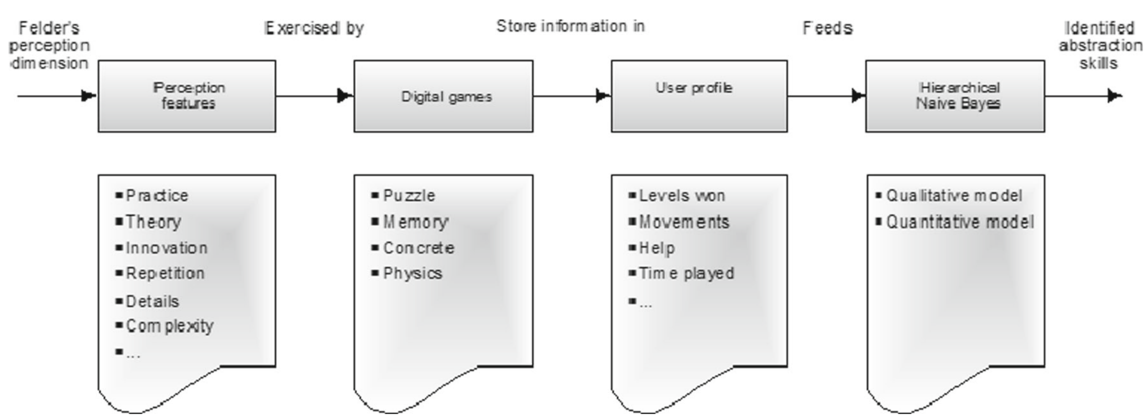

Fig. 1 Proposed approach for identifying skills to manage abstractions by using digital games

(speculation, imagination, hunches). Thus, sensitive people like to learn facts, data and experimentation: learn by doing. They tend to solve problems by standard methods and are more patient with details and repetition than intuitive people. Furthermore, sensitive people are good at memorizing facts. In contrast, intuitive people prefer to learn abstract concepts, principles and theories. They like to discover new solutions and tend to be more innovative and creative than sensitive people. When solving problems, intuitive learners welcome complications and surprises. They are also good at grasping new concepts, tend to be quicker, and feel more comfortable with symbols than sensitive people.

The processing dimension describes complex mental processes in which perceived information is converted into knowledge. According to this dimension, people that do not learn much in situations that require them to be passive, work well in groups, and tend to be experimentalists are considered *active*. In contrast, *reflective* people do not learn much in situations that provide no opportunity to think about the information being presented, work better by themselves, and tend to be theoreticians.

The input dimension deals with people's preferred source of information. This dimension differentiates people that remember best what they *see* (e.g. pictures, diagrams, demonstrations) from *verbal* people, who remember much of what they hear, get a lot out of discussion, prefer verbal explanations, and learn effectively by explaining things to others.

The fourth dimension describes the sequential and global ways of understanding. Thus, *sequential* people follow linear reasoning processes when solving problems and can work with material when they understand it partially or superficially. In contrast, *global* people make intuitive leaps and may be unable to explain how they came up with solutions. They may also have great difficulty understanding partial information.

2.2 Felder's ILS questionnaire

To identify learning preferences, Felder and Soloman created the Index of Learning Styles (ILS) questionnaire.[1] The ILS is a 44-item questionnaire that quantifies people's learning preferences. The questionnaire is divided into 4 groups of 11 questions each, one group for each of Felder's dimensions. Thus, people's learning preferences are expressed with values between +11 to -11 per dimension, with steps +/-2. If a person's score in the perception dimension is between -3 to +3, he/she is fairly well balanced on the dimension exhibiting standard skills to manage abstractions. On the other hand, if the score is between -5 to -11 the person can manage abstractions readily, whereas a value of 5 to 11 represents a person with lack of skills to manage abstractions [15].

2.3 Features of Felder's perception dimension

As we mentioned above, skills to manage abstractions are described by Felder's perception dimension. We decided to analyze abstraction skills from the perception dimension perspective mainly because it has been shown that the perception dimension is correlated with career preferences and aptitudes. Thus, learning preferences are expected to influence students' tendencies to gravitate toward certain fields of study. For example, students who choose to major in a relatively abstract field such as mathematics or physics are expected to be intuitive, while students who choose more practical fields such as civil engineering or nursing are more likely to be sensitive [15].

Felder enumerates several features within the perception dimension:

- **Practice**: Sensitive people prefer to learn by experimentation.
- **Theory**: Intuitive people prefer to learn abstract concepts, principles and theories.
- **Standard methods**: Sensitive people like to solve problems by applying standard methods, such as arithmetic or logic operations.
- **Innovation**: Intuitive people tend to be innovative and creative.
- **Repetition**: Intuitive people do not like repetition.
- **Surprise**: Sensitive people do not like surprises.
- **Details**: Sensitive people are patient with details.
- **Complexity**: Intuitive people welcome complications.
- **Memorization**: Sensitive people are good at memorizing facts.
- **New concepts**: Intuitive people are good at grasping new concepts.
- **Velocity**: Intuitive people tend to be quicker than sensitive people.
- **Symbols**: Intuitive people feel more comfortable with symbols than sensitive people.

In Table 1, we summarize the perception features and indicate whether the person likes (+) or dislikes (-) that feature according to his/her learning preferences.

[1] https://www.engr.ncsu.edu/learningstyles/ilsweb.html

Table 1 Perception features by learning preference

Sensitive	Intuitive
Practice (+)	Practice (−)
Theory (−)	Theory (+)
Standard methods (+)	Standard methods (−)
Innovation (−)	Innovation (+)
Repetition (+)	Repetition (−)
Surprise (−)	Surprise (+)
Details (+)	Details (−)
Complexity (−)	Complexity (+)
Memorization (+)	Memorization (−)
New concepts (−)	New concepts (+)
Velocity (−)	Velocity (+)
Symbols (−)	Symbols (+)

A plus sign (+) indicates preference for the perception feature, whereas a minus sign (−) indicates lack of preference

3 Digital games and players' skills

Digital games are effective at improving performance across a wide range of skills even when they were not specifically built to do that [5]. In recent years, more and more research has been carried out in the digital game field, proving that digital games are a medium where learning arises from tasks simulated by the content, and where skills are developed as a result of playing [31]. It has been proven that people acquire new knowledge and complex skills by playing [6, 25], suggesting gaming could help prepare a new generation of workers for 21st century jobs [7, 10].

There is a wide range of essential skills that can be trained by digital games, such as problem solving, sequencing, deductive reasoning, memorization, and collaboration. In this context, we claim that digital games are a promising tool for exercising and identifying players' skills. We think that digital games can solve many problems associated with traditional skills questionnaires, such as lack of internal consistency, difficulty motivating people to fill them out, lack of awareness of the consequences or future uses of questionnaires, and non-intentional influences in the way the questions are formulated.

A very important aspect of digital games is that many of them already embody sound learning theories in their designs, even if the incorporation of these theories was not deliberate [4]. Particularly, Felder's perception dimension is well supported within digital games [3, 16], since most video games require players to learn facts and understand processes (sensitive) but also to understand concepts and synthesize relationships (intuitive).

In order to detect skills to manage abstractions by using digital games, it is necessary to determine what kind of video games are most suitable for carrying out this task. Thus, we have classified digital games into the following four categories, by taking into account the perception features associated with them:

- **Puzzle**: This type of digital game presents complex problems that cannot be solved in a predetermined way. Instead, players have to use their innovation to figure out how to solve them. In this context, we consider that puzzle games evidence players' *innovation*, their preferences for solving *complex* problems, and their reactions to *surprises*.
- **Memory**: This type of digital game exercises players' memory capacity. Memory digital games present repetitive problems that require players to pay attention to details that have to be memorized. Therefore, we consider that memory games allow us to observe players' *memorization* skills, their behavior when focusing on *details*, and their preference for solving *repetitive* problems.
- **Concrete**: Concrete digital games are video games that can be solved by using standard methods such as arithmetic, algebraic or logic operations. This type of game is characterized by being repetitive since the problems presented are solved by applying the same method over and over again. We think that concrete games allow us to evaluate players' preferences for solving *repetitive* problems through *practice*, and their capacity to apply *standard methods* to find out a solution.
- **Physics**: Physics digital games are video games that aim to teach abstract concepts and interpret symbols. In this context, we consider that physics games allow us to observe players' preference for *theory*, their capacity for working with *symbols*, and their ability to understand *new concepts*.

To summarize, we have classified digital games into four categories related to several perception features. As we explain below, despite their differences, all the digital games implemented in this work have some common functionality. This means that all digital games are divided into levels whose complexity increases as the player advances in the game. Furthermore, each level of the game has a timer that indicates the available time that the player has to solve the current level. If the player does not solve the problem in the given time (timeout), he/she loses the game and must start over. In addition, all digital games have a help menu that explains the game rules and objectives.

Finally, Table 2 summarizes the relationship between the proposed digital game categories and their perception features. It is worth noting that the perception feature *velocity* is associated with the four types of games, since as we already explained, all digital games have a timer that can be used to measure this perception feature.

4 Modeling abstraction skills by using digital games

The first step required to model abstraction skills is to decide which information gathered from the interaction between players and digital games is relevant for abstraction skills detection. In other words, we need to specify the information that will be stored in the user profile that best describes his/her abstraction skills. Then, once the user profile is defined, the next step consists in building a model that receives the collected information stored in the user profile to identify the abstraction skills. Thus, in the next subsections, we explain which information is gathered in the user profile and how the model is built and used to infer players' abstraction skills.

Table 2 Digital games categories and their perception features

Digital game category	Perception feature
Puzzle	Innovation
	Complexity
	Surprise
	Velocity
Memory	Memorization
	Details
	Repetition
	Velocity
Concrete	Practice
	Standard methods
	Repetition
	Velocity
Physics	Theory
	New concepts
	Symbols
	Velocity

4.1 User profile

A user profile is a description of someone containing the most important and interesting facts about him or her that are essential for an intelligent application [34]. To build a user profile, we collect the following information from digital games:

- *Number of levels won*: This field counts the number of levels won by a player in a game.
- *Number of levels lost*: This field counts the number of levels lost by a player in a game.
- *Time played*: This field represents the time spent by a player in a game.
- *Average time played by game level*: This field represents the average time spent by a player in a game level.
- *Maximum level reached*: This field represents the maximum level completed by a player in a game.
- *Number of times played*: This field counts the number of times a player has played a game.
- *Number of times the game ended by a timeout*: This field counts the number of times the player has lost a game by a timeout.
- *Number of movements*: This field counts the number of movements the player performs during a game.
- *Number of times the player accesses the game's help*: This field counts the number of times the player accesses the game's help.

We define the user profile by taking into account which information gathered from the user gameplay can be used to evaluate every game feature. Thus, taking into account puzzle games, we think that *innovation* can be evaluated by analyzing the number of levels won, the maximum level reached, and the number of movements. By intuition, we expect that innovative players will win a greater number of levels, thus completing the game. In addition, we think that players who like innovation will tend to perform a greater number of movements by searching new solutions. Similarly, we evaluate the preference for *complexity* by observing the number of times the player reads the game's help, the number of times the game ends by a timeout, and the number of levels lost. We think that players that frequently access the game's help and lose repeatedly by giving a wrong answer or reaching a timeout will not welcome complications.

Regarding memory games, we think that *memorization* can be evaluated by analyzing the number of levels won and the maximum level reached. Thus, we expect that players who like to memorize things will win more times and will complete the game. In addition, we evaluate players' patience with *details* by observing the average time played by level and the number of levels lost. In this way, we expect that users that play a higher average time by level and lose fewer times will be more patient with *details*. Similarly, we evaluate the players' preference for *repetition* by observing the time spent in the game and the number of times played. Thus, we expect that players who like to solve repetitive tasks will devote more time to play memory games.

With respect to concrete games, we evaluate the players' preference for *practice* by analyzing the number of times played, since we expect players who like to learn by practicing will play this type of game many times. In the same vein, we evaluate the preference for *repetition* by observing the time played because we expect players who like repetition to play for a longer time. Additionally, we evaluate the preference for *standard methods* by analyzing the number of levels won. We expect that players who like to solve problems by applying standard methods will win many times.

Concerning physics games, we think that players' preference for *theory* can be evaluated by analyzing the number of times played. Thus, we expect that players who prefer to learn theory will play physics games many times. In addition, we analyze players' preference for *new concepts* by observing the average time played by level, since we expect that players who devote less average time to move on to the following level are able to grasp new concepts easily. Similarly, we evaluate players' preference for *symbols* by observing the maximum level reached and the number of levels won. Thus, we expect that players who are more comfortable with symbols will reach the final level of the game and will win many times.

Regarding the velocity feature, we analyze the average time played by level. Intuitively, we expect that players who like velocity will solve the levels of the game in less time. Also, we decided not to take into account the surprise feature since we consider that it cannot be inferred by using the registered information. It is important to note that the user profile for a particular student consists of one registry containing the information described above. In this way, the numbers gathered for all games are added by game category. To summarize, in Table 3, we show the information collected in the user profile for every perception feature in every digital game category.

Table 3 User profile information by perception feature and game category

Information	Perception feature	Digital game category
Levels won	Innovation	Puzzle
Maximum level		
Movements		
Help	Complexity	
Timeout		
Levels lost		
Levels won	Memorization	Memory
Maximum level		
Average time played by level	Details	
Levels lost		
Time played	Repetition	
Times played		
Times played	Practice	Concrete
Time played	Repetition	
Levels won	Standard methods	
Times played	Theory	Physics
Average time played by level	New concepts	
Maximum level	Symbols	
Levels won		
Average time played by level	Velocity	All

4.2 Abstraction skills model

As previously mentioned, we model skills to manage abstractions by using a Hierarchical Naive Bayes (HNB) network. Bayesian networks are compact, expressive representations of uncertain relationships among parameters in a domain. A Bayesian network $N = (X, G, P)$ consists of [23]:

- a directed acyclic graph, $G = (V, E)$ with nodes $V = \{v_1, ..., v_n\}$ and directed links E.
- a set of discrete random variables, X, represented by the nodes of G.
- a set of conditional probability distributions, P, containing one distribution for each random variable $X_v \in X$.

As Bayesian networks most often represent causal statements of the kind $X \rightarrow Y$, where X is a cause of Y and where Y often takes the role of an observable effect of X, which typically cannot be observed itself, we need to derive the posterior probability distribution $P(X|Y = y)$ given the observation $Y = y$ using the prior distribution $P(X)$ and the conditional probability distribution $P(Y|X)$ specified in the model. The posterior probability distribution can be calculated by using Bayes' theorem:

$$P(X/Y = y) = \frac{P(Y = y/X)P(X)}{P(Y = y)} \tag{1}$$

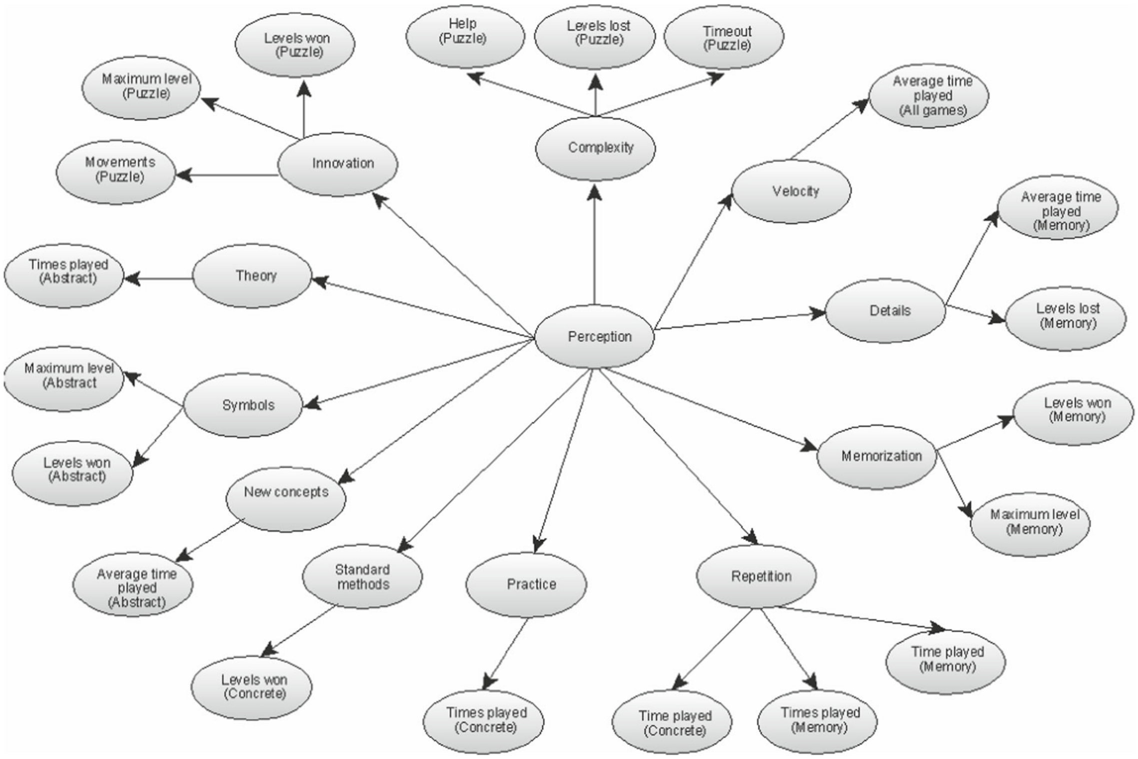

Fig. 2 Hierarchical Naive Bayes network for identifying skills to manage abstractions

where $P(Y = y) = \sum_x P(Y = y/X = x)P(X = x)$. Bayes' theorem plays a central role in statistical inference because the probability of a cause can be inferred when its effect has been observed [26]. In other words, our proposal states that we can infer skills to manage abstractions (cause) by observing people's actions when playing digital games (observable effect). We decided to model abstraction skills with an HNB network for several reasons. First, Bayesian networks provide an intuitive and compact representation of cause-effect relations, allowing us to easily map the relations among the variables enumerated in Felder's model. Second, Bayesian networks provide a coherent and mathematically sound handling of uncertainty, making it possible to infer unobserved variables (abstraction skills) from evidence (playing data). Finally, once constructed, the parameters of a Bayesian network may be continuously updated according to the observed facts [37]. Thus, the initial parameter values will gradually improve themselves as the model gets presented with more and more cases containing a user's playing information. In this way, our approach could be integrated into a Learning Management System to help students to improve their abstraction skills.

To build a HNB network, we have to define both the qualitative and quantitative models. The qualitative model specifies the variables of the domain represented by networks' nodes and the relationship among these variables represented by networks' links. Thus, Fig. 2 shows the structure of the proposed HNB model. Basically, the HNB network is composed of a central node called *perception,* which represents the abstraction skills of a person, that is to say, whether he/she is able to manage abstractions easily (intuitive), has standard abstraction skills (neutral), or exhibits lack of skills to manage abstractions (sensitive). The perception node is also related to every perception feature enumerated in Felder's model and summarized in Table 1. In the same vein, the perception features are related to the user profile information (observable variables) gathered from the digital games that we summarized in Table 3. Once the network variables and the relations among these variables are identified, the last step to define the qualitative model is to identify the states of every variable. Thus, the perception variable defines three states: intuitive, neutral, and sensitive according to Felder's perception definition. Similarly, perception feature variables define three states:

preference, mean preference, and lack of preference, to identify a user's preference, indifference, or lack of preference, respectively. Finally, observable variables define three states: low, medium, and high discretized by uniform count algorithm [24].

To define the quantitative model,[2] we must specify the network parameters, that is to say, the probability distribution of every node. There are three approaches that can be used to define networks' parameters: using expert knowledge, learning from data, or a combination of both. By following the reasoning described in Section 4.1, we use expert knowledge to define the initial values of the probability distribution of every node. Then, we use the learning from data approach to update the probability distributions by using the algorithm Expectation-Maximization [8].

5 Experimental results

We evaluated our approach for three years in the context of two courses, namely Exploratory Programming and Software Engineering. Of a total of 275 enrolled students, 147 participated in the experiments by completing the ILS questionnaire and playing. During the first year, we carried out an initial experiment with 37 Software Engineering students. Then, during the following two years, we conducted two additional experiments in the Exploratory Programming course, with 55 students participating in each of them. We merged the collected data over the three-year period in order to have a more general dataset. It is important to stress that the same digital games were used to collect information from students' gameplay during the three years. In total, students played 8849 levels with a play time of 87 hours, 16 minutes and 37 seconds. On average, each user played 60 levels (8849/147) for 35 minutes and 38 seconds (87:16:37/147), and played 5 games from the 13 that were available. Of the 147 students, 117 (80 %) played at least one puzzle game, 97 (66 %) played at least one memory game, 92 (63 %) played at least one concrete game, and 119 (81 %) played at least one physics game.

To set up the experiments, we assigned students a username and password to a website where the digital games were published.[3] During the first login, students were asked to fill out Felder's ILS questionnaire in order for us to know their skills to manage abstractions. Once a student submitted the questionnaire, he/she was allowed to play any of the 13 digital games published. It is important to note that the students were not forced to complete the questionnaire or to play any particular game. In other words, students were free to choose which games they wanted to play. Figure 3 shows the distribution of students' skills to manage abstractions according to Felder's ILS. Of the 147 students, 20 were able to manage abstractions easily (14 %), 65 had standard abstraction skills (44 %), and 62 exhibited lack of skills to manage abstractions (42 %). We list the students' responses to the ILS questionnaire in the Appendix.

We evaluated the proposed model by applying leave-one-out-cross-validation [20, 28]. Thus, the dataset was split in N subsets of size 1. In this way, we had 147 subsets, one for each student. During the training phase, the HNB model was trained with the information of N - 1 subset. Then, during the testing phase, the model was evaluated by using the remaining subset. The testing phase consisted in entering the information collected in the user profile for the nodes representing the observable variables. Thus, the skills to manage abstractions were inferred by selecting the state (intuitive, neutral, sensitive) in the perception node with the highest probability. For example, in Table 4, we show the probability distribution of the observable variable *number of levels won* for puzzle games. We obtained this probability distribution after taking the first subset (test subset) of the dataset and training the model with the remaining 146 subsets (training subsets). Then, the evidence was fed into the model by setting the state of the observable variables with the test subset information. Table 5 shows the prob-

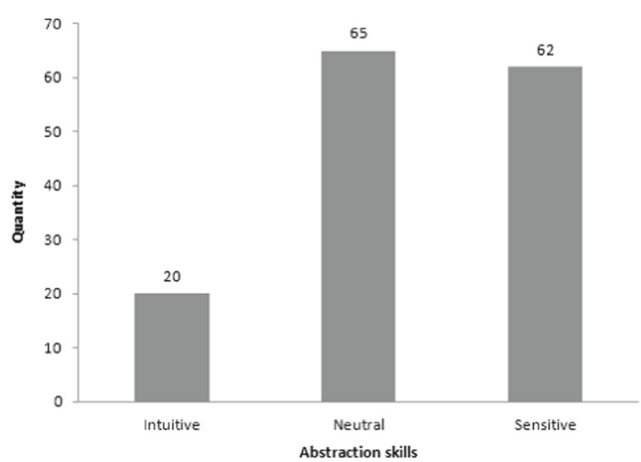

Fig. 3 Distribution of students' skills to manage abstractions

[2] The model and dataset are available at https://github.com/juanfeldman11/abstraction-skills

[3] http://game2d-unicen.rhcloud.com

Table 4 Probability distribution of the observable variable number of levels won in puzzle games

		Perception feature preference		
		No preference	Mean preference	Preference
Number of	Low	0.82	0.0081	0.0017
Levels won in	Medium	0.18	0.98	0.034
Puzzle games	High	0.0027	0.016	0.96

ability distribution of the perception node after setting the evidence. In this way, the model indicates that there is a probability of 52 %, 47 % and 1 % that the student manages abstractions easily (intuitive), has standard abstraction skills (neutral), or exhibits a lack of skills to manage abstractions (sensitive), respectively. Thus, we classify the student as intuitive, since it is his/her most probable abstraction skill.

Results were evaluated by using the standard definitions of precision, accuracy, and error metrics [38]. Table 6 shows the confusion matrix obtained for the proposed approach. In brief, we obtained the lowest precision identifying students that can manage abstractions easily (73 %). The precision for identifying students with standard abstraction skills was 75 %, whereas the precision for identifying students with lack of skills to manage abstractions was 91 %. We consider that the error in the identification of standard and strong abstraction skills was due to neutral students' behavior. As Felder states [15], students with standard abstraction skills tend to change their behavior, exhibiting weak and strong abstraction skills interchangeably. Regarding the accuracy, we obtained a value of 81 %, which we consider a promising result showing that digital games may help identify abstraction skills.

In order to analyze the initial expert settings of the probability distributions, we compared our results with two baselines. For the first baseline, we used a uniform probability distribution, which means that every variable state is equally likely. For the second baseline, we used a randomized probability distribution. We obtained an accuracy of 44 % and 77 % (average of 30 runs) for the uniform and

Table 5 Probability distribution of the perception variable

Intuitive	0.52
Neutral	0.47
Sensitive	0.01

randomized baselines, respectively. Thus, the initial settings of the probability distributions played an important role in the identification of abstraction skills. In addition, we ran another test by disabling the Expectation-Maximization (EM) algorithm in order to evaluate its significance. In this case, the accuracy dropped to 40 %, which highlights the importance of updating the probability distributions during the classification task.

Furthermore, we analyzed the behavior of our approach when classifying students that only played one or two categories of games. Thus, we identified 52 students that played such types of games. These 52 students were correctly classified by our approach. Particularly, 7 students out of the 52 were intuitive and only played abstract and puzzle games. In this way, intuitive students only played games with features that matched their abstraction skills. In contrast, the remaining 45 students (19 neutral and 26 sensitive) played games of diverse categories. Thus, the game choice of an intuitive student could be an indicator of his/her abstraction skills. However, given that this finding is based on a very limited number of cases, the results should be treated with caution.

6 Related research on skills identification

There is a vast amount of literature on the topic of skills identification and development [2, 21, 29]. Particularly, in the field of education, skills identification has been carried out by detecting students' learning styles [19, 33]. Basically, a learning style is a distinctive and habitual manner of acquiring knowledge, skills or attitudes through study or experience [30]. Thus, proposed approaches for identifying skills related to learning styles build user profiles by observing students' behavior when interacting with online educational systems [9, 18]. These approaches address problems associated with traditional skills questionnaires, such as lack of awareness of students' learning preferences; supplementary amount of work on the part of the student; and non-intentional influences in the way the questions are formulated. However, we observe some limitations on the applicability of these approaches. First, in order to identify students' skills, educational systems must provide a wide variety of educational content in different formats. Second, previous works have demonstrated that students' inexperience working with educational systems modifies their behavior, hindering the skills detection [17, 18]. Lastly, students are not usually motivated to use educational systems since they include traditional learning material that is static and boring.

Table 6 Confusion matrix for the proposed approach

		ILS abstraction skills			
		Intuitive	Neutral	Sensitive	Precision
Identified abstraction skills	Intuitive	14	4	1	73 %
	Neutral	6	56	12	75 %
	Sensitive	0	5	49	91 %
	Accuracy	81 %			
	Error	19 %			

In this work, we propose an approach based on digital games to address the limitations of current learning style identification techniques. In this way, we focus on abstraction skills identification by applying a Hierarchical Naive Bayes classifier fed with the information collected in the user profile. Previously, in [16], we presented a preliminary work for detecting Felder's perception style by using a digital game. In that earlier work, we proposed a simple Naive Bayes model to build the user profile that was fed with the information gathered from a single puzzle game. A major drawback of our previous work was its simplicity, since it only took into account one game and 4 variables to identify students' perception style. In addition, no attention was paid to the perception features enumerated in Felder's model. Thus, in this work, we analyze students' abstraction skills by taking into account 11 perception features, determining which type of digital games are more suitable for abstraction skills identification, and including further experiments by increasing the number of participants.

7 Conclusion and future work

We have presented an approach to identity abstraction skills by using digital games. We have based our research on Felder's model, which is one of the most referenced frameworks in the literature. The findings of this study suggest that digital games can help us identify skills to manage abstractions. Thus, we have devised a procedure that consists of collecting information generated from several digital games. The information is stored in a user profile to feed a Bayesian network classifier, which categorizes a person as able to manage abstractions readily (intuitive), having standard abstraction skills (neutral), or having difficulty managing abstractions (sensitive). In this way, our main goal was to identify a person's abstraction skills, due to their relation to career preferences and aptitudes. Thus, one potential application of our approach would be to use it in career counseling. We also think that our approach does not suffer from the problems associated with traditional skills questionnaires (enumerated in Section 3), and therefore it represents a viable alternative. Moreover, we consider that it is not necessary for a user to play all the games for his/her abstraction skills to be inferred. As we mentioned in Section 5, every user played 5 games on average, which is a small number of games as compared with the 13 games available online.

We analyze and highlight some limitations of our work. First, the approach is sensitive to the number of times a student plays; therefore, if a student plays few times, the information used to feed the HNB model is insufficient to determine abstraction skills correctly. However, we observed that this behavior did not occur frequently since our digital games were implemented to be used as advergames [1], that is to say, during students' free time over small periods of time. Second, people with standard skills to manage abstractions can introduce noise into the dataset. Thus, as pointed out by Felder [15], people with standard skills are expected to change their behavior, sometimes managing abstractions readily, sometimes having difficulty managing them. This could lead to masking skills differences that might appear in people with stronger/weaker skills. For this reason, Felder advices to only examine students with strong/weak abstraction skills (intuitive and sensitive). However, we decided to take into account students with standard skills to manage abstractions since most of the students that participated in the experiments belong to that group. This decision might have introduced a bias in the classification, but it also allowed us to take into account all the students.

We are currently researching how to enhance our model by adding new variables and games to improve the accuracy of our approach. Our objective is to improve abstraction skills identification. In addition, in order to further our research, we plan to extend our approach to other dimensions of Felder's model.

Appendix

Table 7 Students' responses to Felder's ILS questionnaire

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	perception
1	B	B	A	A	B	B	B	B	A	B	B	B	A	B	A	B	A	B	A	A	B	B	A	B	B	B	B	B	B	B	B	B	A	B	B	B	A	B	A	B	A	B	A	B	−11
2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	B	B	B	B	B	B	B	B	−11
3	A	B	B	B	B	B	B	B	A	B	B	A	B	B	B	B	B	B	B	A	B	B	A	A	B	B	A	B	B	A	B	A	B	B	B	B	A	B	B	A	A	B	B	A	-9
4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	A	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	B	-9
5	B	B	B	B	B	B	A	B	A	B	B	A	B	A	B	A	B	B	A	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	B	A	B	A	B	-9
6	B	B	A	B	B	B	A	A	A	B	A	A	A	B	B	A	B	B	A	B	A	B	A	B	B	A	A	B	B	B	A	B	A	B	A	B	A	B	B	B	A	B	A	B	-9
7	A	B	A	B	A	B	A	B	B	B	A	B	A	B	A	B	B	B	A	B	B	B	A	B	A	A	A	B	A	B	A	B	B	A	B	A	A	B	A	B	B	B	A	A	-7
8	A	B	A	B	A	B	B	B	A	B	B	A	A	B	B	B	A	B	B	A	A	A	A	B	B	B	A	B	A	B	A	B	A	B	B	B	A	B	A	A	A	A	A	A	-7
9	B	B	A	B	A	B	A	B	A	A	B	B	B	B	A	B	A	B	A	A	B	A	A	B	B	B	A	B	A	B	A	B	B	B	A	B	B	B	B	A	B	B	B	B	-7
10	A	B	A	B	A	B	A	B	A	B	A	A	A	B	A	B	B	B	A	A	A	B	A	B	B	A	A	B	A	B	A	B	A	B	B	A	A	B	B	B	A	A	B	B	-7
11	B	B	A	B	A	B	A	B	B	B	A	B	B	B	A	A	B	B	A	B	B	A	A	B	B	B	A	B	A	B	A	B	A	A	B	B	B	B	A	B	B	B	A	B	-7
12	A	B	A	B	A	B	A	B	A	B	A	A	A	B	A	B	B	B	A	A	A	B	A	B	B	A	A	B	A	B	A	B	A	B	B	A	A	B	B	B	A	A	B	B	-7
13	A	B	A	B	A	B	A	A	B	A	A	A	B	B	B	A	A	B	A	B	B	B	A	B	A	B	A	B	B	B	A	A	A	B	A	B	A	A	B	B	B	B	A	A	-7
14	B	B	A	A	B	B	A	A	B	B	A	A	B	B	A	A	B	A	A	B	B	B	A	B	B	B	A	B	A	B	A	A	B	A	A	B	B	A	B	B	A	B	A	A	-5
15	B	B	A	A	B	A	A	B	A	B	A	B	A	A	A	B	A	B	A	B	A	B	A	A	B	A	A	B	B	B	A	A	A	B	A	B	A	B	B	B	A	B	A	B	-5
16	A	A	A	B	A	A	A	A	A	A	B	B	A	B	A	A	A	A	B	B	A	B	A	B	A	B	B	B	B	A	B	B	A	B	A	B	A	A	A	A	A	A	A	A	-5
17	B	B	A	B	A	B	A	B	A	A	B	B	B	B	B	A	B	B	A	B	B	B	A	B	B	B	B	B	B	B	A	A	A	B	A	B	B	B	A	A	A	A	B	B	-5
18	A	B	A	B	A	A	A	A	A	B	A	A	A	B	A	A	A	B	A	B	A	B	A	B	B	B	B	B	B	B	A	B	A	A	A	A	A	B	B	A	A	A	A	B	-5
19	A	B	A	B	B	B	A	A	B	B	A	A	A	A	B	A	A	B	A	B	B	B	A	B	B	B	A	B	A	A	A	B	B	B	A	B	A	A	A	B	A	B	A	B	-5
20	B	B	A	B	A	A	A	A	A	B	A	B	A	B	B	A	B	A	B	B	A	B	A	B	B	B	A	B	B	B	A	A	A	B	B	B	A	A	B	B	A	B	A	A	-5
21	A	B	A	B	A	A	B	A	B	A	B	A	A	B	B	A	B	A	B	A	A	A	A	A	B	B	B	A	A	B	A	A	A	B	B	A	A	B	B	A	A	A	A	B	-3
22	A	A	A	B	B	B	A	B	A	B	A	A	A	B	A	A	B	B	A	B	B	B	A	B	B	A	A	B	B	B	A	B	B	A	B	B	A	B	A	B	A	A	A	A	-3
23	B	B	A	B	B	B	A	A	B	B	A	B	A	B	A	A	B	A	A	A	A	A	B	B	B	A	B	B	A	B	A	B	B	A	B	B	A	B	B	A	B	B	B	B	-3
24	B	B	A	B	B	B	B	B	A	B	B	A	B	A	B	B	A	B	A	A	B	A	A	A	B	A	B	B	B	B	B	A	A	A	A	B	B	B	B	A	A	B	A	A	-3
25	B	B	A	B	B	A	A	A	A	B	A	A	A	B	B	A	B	B	A	B	B	B	A	A	B	B	B	B	A	A	A	A	A	B	B	A	A	A	B	A	A	A	A	B	-3
26	B	B	A	A	A	B	B	A	A	B	B	B	B	B	B	A	B	A	A	A	A	A	A	A	B	B	A	A	B	A	B	A	A	B	B	B	B	B	A	A	B	A	B	A	-3
27	A	B	A	B	A	A	B	B	A	A	A	A	B	A	A	A	A	A	A	B	A	B	A	B	A	B	B	B	A	B	A	A	A	B	B	B	A	A	A	B	A	B	A	B	-1
28	A	B	A	A	B	B	A	A	B	A	B	A	B	B	B	A	B	A	A	A	B	A	B	B	B	B	B	B	B	B	B	B	B	A	B	B	B	A	B	A	B	B	A	A	-1
29	A	B	A	B	A	A	A	B	A	A	A	B	A	B	B	A	B	A	A	B	A	B	A	B	B	A	A	B	A	B	A	A	A	B	A	B	A	A	B	A	A	B	A	B	-1
30	A	B	A	A	A	B	A	A	A	B	B	A	A	A	B	A	B	A	A	A	B	B	A	A	B	A	A	B	B	A	A	A	B	B	A	A	B	B	B	B	B	A	A	A	-1
31	A	A	A	A	A	B	A	B	A	A	A	A	B	A	A	B	B	A	A	B	B	A	A	B	A	B	A	B	B	B	A	B	B	B	A	B	B	B	B	B	A	B	A	B	-1
32	A	A	A	B	A	A	B	B	A	B	A	A	A	B	B	A	B	A	B	A	A	B	A	B	B	B	A	B	A	B	A	B	A	B	A	B	A	A	A	A	A	A	B	A	-1
33	A	A	A	B	A	A	A	A	A	A	B	A	B	B	B	A	B	A	A	B	A	B	B	B	A	B	B	B	A	A	A	B	A	B	A	B	A	B	A	A	A	B	A	B	-1
34	A	A	A	B	B	A	A	B	A	B	A	A	A	B	A	B	B	B	A	A	B	B	A	A	B	B	A	B	A	A	A	B	B	A	A	B	B	B	B	A	A	A	A	A	-1
35	B	A	A	B	A	A	A	A	B	A	A	A	B	A	A	B	B	A	A	A	A	B	B	B	A	A	B	B	A	A	A	B	B	A	A	A	B	A	B	A	A	B	A	A	-1

Table 7 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	perception
36	B	A	A	B	B	B	B	A	A	B	B	A	B	A	B	A	A	B	B	A	B	A	A	A	B	B	B	B	A	A	B	B	B	A	B	A	A	B	A	B	B	B	A	A	-1
37	A	B	A	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	B	A	B	A	B	B	B	A	B	A	B	A	B	B	B	A	A	A	B	A	B	A	B	-1
38	B	A	A	B	B	B	A	B	A	B	B	B	A	A	B	A	B	B	A	A	A	A	A	B	B	A	A	B	A	B	A	A	A	A	A	B	B	B	A	A	A	B	A	A	-1
39	B	B	A	B	B	A	A	B	A	A	A	B	B	B	B	B	B	B	A	B	B	A	A	B	B	B	A	B	B	B	B	B	A	A	B	A	B	B	B	B	A	A	A	B	-1
40	A	B	A	B	A	A	A	A	A	A	A	A	A	B	A	A	B	A	A	A	B	B	A	B	A	B	A	B	A	A	A	A	B	B	B	B	A	A	A	A	A	A	A	A	1
41	A	A	A	B	B	A	A	B	B	B	B	B	A	B	A	A	A	A	B	A	A	A	A	A	B	B	B	A	A	A	B	A	B	B	B	B	B	A	B	B	A	B	A	B	1
42	A	B	A	B	A	A	B	B	A	A	B	B	B	B	B	A	B	A	A	A	B	A	A	B	B	B	A	B	A	B	A	B	A	B	B	A	B	A	B	A	A	A	A	B	1
43	A	A	A	B	B	A	B	A	A	A	B	A	B	B	B	B	A	A	A	B	A	B	A	B	A	B	A	A	B	A	B	B	A	B	B	A	B	A	B	A	A	B	A	B	1
44	A	B	A	B	B	A	A	B	A	A	A	A	A	B	A	A	B	A	A	B	A	B	A	B	B	A	A	B	A	B	A	B	A	B	B	B	A	A	A	B	A	A	A	B	1
45	A	A	A	B	B	A	A	B	B	B	B	B	A	B	A	A	A	A	B	A	A	A	A	A	B	B	B	A	A	A	B	A	B	B	B	B	B	A	B	B	A	B	A	B	1
46	B	A	A	B	B	B	B	A	A	B	A	A	B	A	B	A	B	B	A	A	B	A	A	A	B	A	B	B	B	B	B	A	A	A	B	A	B	B	B	A	B	A	B	A	1
47	A	B	A	A	A	A	A	A	A	A	A	A	B	B	A	A	B	A	A	A	A	A	A	B	A	A	B	B	A	B	A	B	A	B	A	B	A	A	A	B	A	B	A	B	1
48	A	A	A	A	A	A	A	A	A	B	A	A	A	A	A	B	B	A	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	B	B	A	A	A	A	A	A	A	B	1
49	B	B	A	B	B	A	B	A	A	A	B	A	B	B	B	A	B	A	A	A	B	B	A	A	B	B	A	B	A	A	B	B	A	B	B	A	B	A	A	B	A	A	A	A	1
50	A	A	A	B	B	A	A	A	B	B	A	A	B	B	A	A	B	A	A	A	A	B	A	B	A	B	A	B	A	A	A	A	B	B	B	B	A	A	A	A	A	A	A	A	1
51	B	A	A	B	A	A	A	B	A	B	A	B	A	A	A	B	A	A	A	B	A	B	A	B	A	A	A	B	B	B	A	B	A	B	A	B	A	A	A	B	A	B	A	A	1
52	A	A	A	B	A	A	B	A	A	A	A	A	B	B	B	A	A	A	A	A	A	A	A	B	A	A	A	B	A	A	A	B	B	B	A	A	A	A	B	B	A	B	A	A	1
53	B	A	A	B	B	B	A	A	B	B	B	A	B	B	B	A	B	B	B	A	B	A	B	A	B	A	B	B	B	A	B	A	A	A	B	A	B	B	B	B	B	A	A	A	1
54	B	A	B	B	B	B	B	B	B	B	B	A	B	A	B	B	B	B	B	B	B	A	B	B	B	B	B	B	A	A	B	B	B	A	B	B	B	B	B	B	B	A	B	B	1
55	A	B	A	B	A	A	A	A	B	A	A	A	B	B	B	A	B	A	A	A	B	A	A	B	A	B	A	B	B	B	A	A	A	B	A	B	B	A	A	B	B	A	A	B	1
56	A	B	B	B	A	A	B	A	B	A	A	B	A	B	B	A	A	A	A	A	A	B	A	A	A	B	A	B	A	A	A	B	A	B	B	B	A	A	A	A	A	A	A	B	1
57	A	B	A	B	B	A	A	B	A	A	B	B	A	B	A	A	A	A	A	A	B	A	A	B	B	B	A	B	A	A	B	A	A	B	A	A	A	A	A	B	A	B	A	A	1
58	B	B	B	A	B	B	B	A	A	B	B	A	B	A	B	B	B	B	B	A	B	A	B	A	B	A	B	A	A	A	B	A	A	A	B	A	B	B	B	B	A	A	B	A	1
59	A	A	A	B	A	A	A	A	B	B	A	A	B	A	B	A	A	B	A	B	A	A	A	B	B	A	A	B	A	A	A	A	A	A	A	B	B	B	B	A	A	A	B	A	3
60	A	A	A	B	B	A	B	A	A	A	A	B	B	B	A	A	A	A	A	A	A	A	A	B	B	B	A	A	B	B	A	A	A	A	A	A	A	A	B	A	B	B	A	B	3
61	B	A	B	A	B	A	B	A	A	B	B	B	A	A	B	B	B	B	A	A	B	A	B	B	A	A	B	A	A	A	B	B	B	A	A	A	A	B	A	A	B	B	B	B	3
62	B	A	B	A	B	B	B	A	B	B	B	A	A	A	B	A	A	B	B	A	A	A	B	B	B	A	B	A	B	A	B	A	A	A	B	A	A	B	B	A	A	A	B	A	3
63	A	A	B	B	B	A	B	A	A	A	A	B	B	B	A	A	A	B	A	A	B	A	A	A	B	A	A	B	A	A	A	B	A	A	B	A	B	B	A	B	A	B	B	A	3
64	B	A	A	B	B	B	A	B	A	A	B	A	A	B	B	A	B	B	A	A	A	A	A	B	B	A	A	B	A	A	A	A	B	A	A	B	A	A	B	A	B	B	A	A	3
65	B	A	B	A	A	A	A	A	A	B	B	B	B	B	B	A	A	A	B	B	B	A	A	A	B	B	B	A	A	B	B	B	B	A	B	B	A	A	A	B	A	A	B	B	3
66	A	B	A	B	B	A	A	A	A	A	A	B	A	B	B	A	A	A	A	A	A	A	A	B	B	B	A	B	A	A	A	B	A	A	A	B	A	A	A	A	A	B	A	A	3
67	A	B	A	B	A	A	A	A	B	A	A	A	A	B	A	B	B	A	A	A	A	B	A	B	B	A	A	B	A	A	B	A	B	B	A	A	A	A	A	A	A	A	A	A	3
68	A	B	A	B	A	A	B	B	A	B	B	B	A	A	A	A	B	A	B	A	A	B	A	B	B	A	B	A	A	A	A	A	A	A	B	B	A	A	A	A	A	B	B	A	3
69	A	A	A	B	A	A	B	B	A	A	B	A	B	A	A	A	A	A	A	B	A	A	A	B	A	A	A	B	A	A	B	B	A	B	A	A	B	B	B	A	A	A	A	A	3
70	A	A	A	A	B	A	B	B	A	A	B	B	B	A	A	A	A	B	A	B	B	A	A	B	A	B	A	B	A	A	A	A	A	B	B	A	B	A	B	A	A	B	A	A	3
71	A	B	A	B	A	A	A	A	A	B	A	A	A	B	B	A	A	A	A	A	A	A	A	B	A	A	A	B	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	3
72	A	B	A	B	B	A	A	A	A	A	B	B	B	A	B	B	B	A	A	A	B	B	A	B	B	B	B	B	A	A	A	B	B	B	B	B	B	A	B	B	A	A	A	B	3

Table 7 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	perception
73	A	A	A	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	3
74	A	A	A	B	A	A	A	A	B	A	A	A	A	B	B	B	B	A	A	A	A	B	A	A	B	B	A	B	B	A	A	B	A	B	A	B	B	A	A	B	A	A	A	A	3
75	A	A	B	B	A	A	B	B	A	A	A	A	B	B	A	A	A	A	A	A	B	B	A	B	A	B	A	B	B	A	B	B	A	A	B	B	A	A	A	A	A	B	A	B	3
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82	A	A	A	B	A	A	B	A	A	B	A	A	A	B	A	A	B	A	A	A	A	A	A	B	B	B	A	B	A	A	B	B	B	B	B	B	A	A	A	B	A	A	A	A	3
83	A	A	A	B	B	A	A	B	A	B	A	A	A	A	B	A	B	A	A	A	A	B	A	B	B	A	A	B	A	B	A	A	A	B	B	B	A	A	A	A	A	A	A	A	3
84	A	A	A	B	A	B	A	A	B	A	B	A	A	A	B	A	B	A	B	A	A	A	A	B	B	B	A	B	A	B	B	A	A	B	B	A	A	A	B	B	A	A	A	A	3
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97	B	B	A	B	B	A	A	A	A	B	A	A	B	A	B	A	A	A	A	A	B	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	5
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107	A	B	A	B	B	A	A	B	B	A	A	B	B	B	A	A	A	A	B	A	B	A	A	B	A	A	B	B	A	A	A	B	A	A	A	A	B	A	A	A	A	B	B	A	5
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109	A	A	B	A	A	A	B	A	B	B	B	A	A	A	B	A	B	A	A	A	A	A	B	A	B	A	A	B	A	B	B	B	A	A	A	B	A	B	A	A	A	A	A	A	5

Table 7 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	perception
110	A	A	A	B	A	A	A	B	A	A	A	A	A	A	A	A	A	A	A	B	B	A	A	B	A	B	A	B	B	A	A	B	A	A	B	B	A	A	A	A	A	B	A	B	7
111	A	A	A	B	A	A	A	A	B	A	A	A	B	A	A	A	A	A	A	B	B	A	A	A	A	A	A	B	A	A	A	B	A	B	A	A	A	A	A	B	A	B	A	A	7
112	A	A	A	B	A	A	B	A	A	B	B	A	A	A	A	A	B	A	A	A	B	A	A	A	B	A	B	B	A	B	A	A	B	A	A	A	B	A	A	A	A	A	B	A	7
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114	A	A	A	A	A	A	B	A	A	B	B	A	B	A	A	A	B	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	B	7
115	A	A	A	B	A	A	A	B	A	A	B	A	B	A	A	A	B	A	A	A	A	A	A	A	A	A	A	B	A	A	B	A	A	B	B	B	A	A	A	B	B	B	A	A	7
116	A	A	A	A	A	A	A	A	B	B	A	A	B	A	B	A	B	B	B	B	B	A	A	B	A	A	B	B	A	A	B	A	A	A	B	B	B	A	A	B	B	A	A	A	7
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122	A	B	A	B	A	A	B	B	A	A	B	B	A	A	B	A	B	A	A	B	A	A	A	B	B	A	B	B	A	B	A	B	A	A	B	B	A	A	A	A	A	A	A	B	7
123	B	A	A	B	A	A	B	B	B	A	B	A	A	A	B	B	B	A	A	A	A	A	A	B	B	B	A	B	A	A	A	B	A	B	B	A	A	A	A	B	A	A	A	A	7
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126	A	A	B	B	B	A	A	A	B	A	A	B	A	A	A	B	B	A	A	A	A	A	A	A	B	A	A	B	A	B	A	A	B	B	B	A	A	A	A	A	A	A	A	A	7
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129	A	A	A	A	A	A	A	A	B	A	A	B	A	A	A	A	B	A	A	A	A	A	A	A	B	A	A	B	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	B	9
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131	B	A	A	B	B	B	B	A	B	B	A	A	B	B	B	A	B	B	A	B	A	A	A	A	B	A	A	B	A	A	A	A	A	A	A	B	B	A	A	A	A	B	B	A	9
132	A	A	A	B	B	A	A	A	A	B	B	B	B	A	B	B	B	A	A	B	B	A	A	B	B	A	A	B	B	A	A	B	A	A	B	B	A	A	B	A	B	A	A	A	9
133	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	B	A	A	A	A	A	B	A	A	B	A	A	A	B	B	A	A	A	A	9
134	A	A	A	B	B	A	A	A	B	A	A	B	B	A	B	B	A	A	A	A	B	A	A	A	A	A	B	B	B	A	A	A	A	A	A	B	A	A	A	A	A	B	A	A	9
135	A	B	A	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	B	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	9
136	A	A	A	B	B	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	A	A	B	B	A	A	A	B	A	A	A	A	A	B	B	A	A	A	A	A	A	A	A	A	9
137	A	A	A	B	A	A	A	B	B	A	B	A	B	A	B	A	B	A	B	A	A	A	A	B	A	A	B	B	A	A	A	A	A	A	B	B	A	A	A	B	B	B	A	B	9
138	A	A	B	B	A	B	A	B	B	A	B	A	B	A	B	B	A	A	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	A	9
139	B	A	A	A	B	A	A	A	A	B	A	A	A	A	B	B	B	A	B	B	B	A	A	A	B	A	B	B	A	A	B	B	A	A	B	B	A	A	A	B	A	A	B	B	9
140	B	A	A	B	B	A	A	B	B	A	A	A	B	A	A	B	B	A	A	A	A	A	A	B	B	B	A	A	A	A	A	A	A	A	B	B	A	A	A	A	B	A	B	A	9
141	A	B	A	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	B	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	9
142	A	A	A	A	A	A	B	A	B	A	B	A	B	A	B	A	B	A	A	A	A	A	B	B	A	A	A	A	B	B	A	A	B	A	A	A	B	A	B	B	A	A	A	A	9
143	A	A	A	A	B	A	B	A	B	A	B	B	B	A	B	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	B	A	B	A	B	A	B	A	B	B	B	A	A	A	11
144	A	A	A	A	A	A	B	A	A	A	A	A	B	A	B	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	B	B	A	A	A	A	A	A	A	B	A	A	A	A	11
145	A	A	A	B	A	A	A	A	B	A	A	A	B	A	B	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	11
146	A	A	A	B	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	B	A	A	A	B	A	A	A	B	A	A	A	B	A	A	A	B	A	A	A	A	A	A	A	A	11
147	B	A	A	B	A	A	A	A	B	A	A	A	B	A	A	A	B	A	A	A	A	A	B	B	A	A	A	B	A	A	B	A	A	A	B	A	A	A	A	B	A	A	A	A	11

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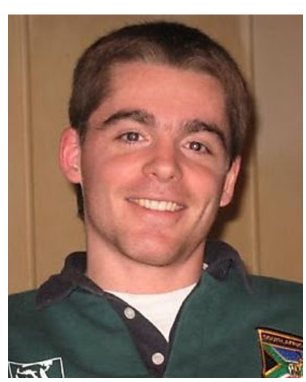

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