Mapping Task Types and Gameplay Categories in the Context of Declarative Knowledge Training

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Abstract: Learning games for the training of declarative knowledge must offer learners a wide variety of game situations in order to keep them engaged. Designing such situations remains a challenge due to the inherent entanglement of didactical objectives and gaming implementations. This article proposes to tackle the need for mapping different training tasks to different gameplays in order to help the design of relevant gameplay-oriented training situations. We identified an approach during the design of a Rogue*lite*-oriented training game for multiplication tables. This approach has been intentionally specified towards a genericity purpose by using domain-independent task types and abstract gameplays. This article details the method we followed to identify this approach and presents the resulting mappings when applied to our specific application context.

1 INTRODUCTION

This last decade, the design and use of *learning games* has become a common practice (Codish and Ravid, 2015). However, most learning games fail to be seen as real video games mostly because of their lack of gameplay (i.e., fun elements that can be controlled, decided and done by the players) (Prensky, 2005). Although combining the fun of real game and educational content is not easy (Prensky, 2005), it is a key component of a good learning game design. Combining the two dimensions (i.e., game and education) is difficult, primarily because there are multiple variables to consider. Moreover, these variables often depend on the knowledge to be learned and the targeted game genre.

Learning games targeting declarative knowledge training require a deeper commitment from learners as they are used regularly for repetitive training sessions. This implies that the design of such learning games must offer a wide variety of situations, game mechanisms or gameplays. Designers then have to deal with various stakes such as the dynamic generation of training sessions or the adaptation of these sessions to take into account the different teachers and/or learners' needs or preferences. This also includes designing how the variety of situations will be tackled.

Our research interest is about that challenge. We focus on it by considering the design of varied gameplays. These gameplays involve that the player-learner makes the avatar, which he/she controls, interact with the environments and objects in the game to perform contextualized actions to answer the question being asked. Because training games include several domain-specific parameterized training tasks, many gameplays have to be identified for each one of them. Identifying how different training tasks can be implemented using these different gameplay concepts requires conceptualizing and addressing a transdisciplinary TEL (Technology Enhanced Learning) problem: how can didactic knowledge be mapped to different gameplays?

We encountered this challenge during the design of a Rogue*lite* oriented learning game to train the retention of the multiplication tables. First, we identified an approach that involves addressing the challenge at a higher level of abstraction (task types instead of domain-specific tasks and game categories instead of practical gameplays). This allows for a more generic and domain-independent approach. Secondly, the main thrust of the approach is to use a dedicated pivot to help identify the source (task types) and target (gameplay categories) parameters whose values will guide the elicitation of practical mappings. This paper explains how we identified this approach (method), what this approach consists in (proposal),

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and which mappings are obtained in our context (application). We assume that this approach is sufficiently generic and reusable to contribute to helping multidisciplinary design teams identify and map gameplays for their domain-specific tasks (contribution).

In cognitive psychology, test-based learning represents the idea that the process of retrieving (i.e. remembering) concepts or facts increases their long-term retention. While tests are mainly used as summative assessment tools, they can also be formative. Repeated retrieval (i.e., retrieval practice) is one way to implement test-based learning, which has been shown to improve long-term retention in research (Roediger and Pyc, 2012; Brame and Biel, 2015). In addition, research also suggests that various test formats enhance learning (i.e. the benefits are not linked to a specific type of retrieval practice) (Brame and Biel, 2015). In our work, *training* means providing the learner with different forms of questions repeatedly, which is a form of retrieval practice.

The structure of this paper is as follows: Section 2 presents our research context including our gaming (Rogue*lite* genre) and learning (training of multiplication facts) contexts as well as the mapping issue; Section 3 draws current close research studies for tackling this challenge; Section 4 details how the identification of the mapping approach we propose has been conducted; Section 5 presents the resulting approach and its application in our specific context; Section 6 discusses the next challenges to overcome, mainly about formalizing and exploiting the resulting mappings to drive the generation of adapted training sessions.

2 RESEARCH CONTEXT

Our research interest is about generating effective and engaging training sessions for the retention of declarative knowledge. Declarative knowledge (i.e. knowledge about facts, laws, statements, etc.) are known to require repetition for encouraging their memorization, generalization, and retention (Kim et al., 2013; Roediger and Pyc, 2012). Our concern is about identifying approaches, models, and processes helping multidisciplinary teams in designing learning games targeting such training. Nevertheless, creating activities combining fun and educational content is not an easy job (Prensky, 2005). To that extent, Prensky proposed a three steps process to create digital game-based learning: "(1) Find or create a game with great gameplay that will engage our audience, (2) Find the learning activities and techniques that will teach what is required (doing each with the other in mind), and then (3) successfully blend the two".

2.1 A Rogue*lite* for Multiplication Tables Training

As a first application domain, our research takes place into the context of the *AdapTABLES* project[1] which aims at designing and developing a learning game for the training of multiplication tables. It implies the design of a generator for providing game levels during training sessions. It is worth notice that practicing multiplication tables will complement classroom learning (from the teacher's point of view): learning the tables, application in problem-solving, and generalization are outside the scope of the learning game. This project involves mathematical teachers and didactic experts, as well as game designers and serious game experts.

In addition, we studied different game *genres* in order to identify those capable of keeping players engaged while providing repetitive but various gameplays. The Rogue*lite* game genre meets these needs. It is mainly characterized by procedural dungeon generation with randomized content, permanent death (each avatar's death implies for the player to start a new playthrough), and limited retention of unlockable game elements (characters, items, powerups, ...).

Hadès, Rogue Legacy, Binding of Isaac are well known Rogue*lite* video games. They also share a dungeon-crawler approach: the player has to explore dungeons made up of interconnected rooms where actions take place. Therefore, Rogue*lite* combines all necessary prerequisites for training declarative knowledge (i.e., generation → variety, repetition, and it is a well-known and liked game genre). Briefly, learners-players will get across successive generated dungeon levels, wherein most of the rooms will challenge them to answer task-oriented questions.

2.2 Abstract Training Task Types

In an exploratory research, partially presented in (Laforcade et al., 2022), a user group composed of 2nd to 6th grade teachers and mathematics experts has identified several tasks for training multiplication tables, such as: complete a fact where the result is missing, complete a fact where the operand is missing, decide if a fact is correct, identify the results of a table. These tasks also embeds dedicated parameters in order to drive which facts to consider, how to build them and how to answer them.

[1] https://projets-lium.univ-lemans.fr/adaptables/

In a perspective of genericity with other domain-related declarative knowledge, we abstracted them into 5 task types:

1. **Completion 1**: complete an incomplete fact that has one missing element (e.g., $3\times? = 15$, $15 = ?\times 5$, $3\times 5 = ?$);
2. **Completion 2**: complete an incomplete fact that has two missing elements (e.g., $?\times? = 15$ with a set of given choices $[3,6,5,10]$, $?\times 5 = ?$ or $3\times? = ?$ also with sets of given choices);
3. **Reconstruction**: replace, in the correct order, all important elements of a fact (e.g., $?\times? = ?$ with a set of given choices $[3,6,5,10,15]$);
4. **Identification**: identify the correctness or incorrectness of one or several facts (e.g., $3\times 5 = 15$, true or false?);
5. **(Non-)Membership Identification**: identify the elements that share or do not share a given property (e.g., $[3,5,9,12,14,21]$ which are results of the table 3?);

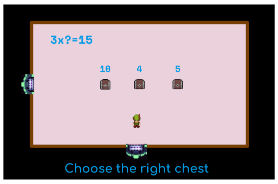
These task types do not claim to be exhaustive. They only cover the specific multiplication tables tasks and are expressed at a higher level of abstraction.

2.3 Abstract Gameplay Types

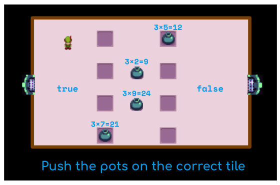
As mentioned by (Prensky, 2005), the main reason for learning game failure is their lack of gameplay. Therefore, we intend to provide a variety of possible gameplays. To that extent, informal interviews were conducted with game designers to gather possible ideas which lead to the design of gameplay mock-ups. A game prototype with a few gameplays was created to test some ideas and collect some feedback. One observation was made after the design of the mock-ups: *some gameplays seemed to belong to the same category* (e.g. breaking the pot wearing the answer and opening the chest wearing the answer are two similar ways of selecting an object). This observation followed the idea of the game classification proposed by (Djaouti et al., 2008) which consists in describing games through gameplay bricks (i.e., categories of actions that can be performed within the games). Consequently, further reflexion led to the definition of 5 categories of gameplay in our context (as for the task types, these categories do not claim to be exhaustive):

1. **SELECT**: select (e.g., touch, kill, break, open) objects wearing the correct answers, through avatar actions;
2. **MOVE**: correctly place objects at specific locations through avatar actions;
3. **ORIENT**: orient objects (e.g., rotate), through avatar actions, towards the correct answer;
4. **POSITION**: move the avatar to the necessary positions for choosing or typing the correct answers;
5. **DIRECT RESPONSE**: no action is required through the avatar, learners can directly type down their answer by using an input device (e.g., enter the correct answer through a keyboard).

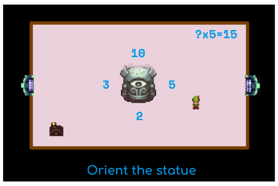
Figure 1 presents a gameplay mock-up for each category.



(a) SELECT example

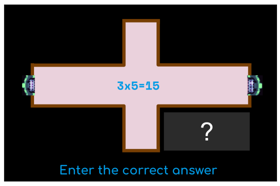


(b) MOVE example



(c) ORIENT example

(d) POSITION example



(e) DIRECT RESPONSE

Figure 1: Example of mock-ups by gameplay categories

2.4 Research Questions

Following Prensky's process, our main question now is: *how to determine and specify the relationships between task types and game categories necessary to the design of learning game activities?* Indeed, knowing these relationships is important at design-time to guide the identification of practical gameplays for every specific tasks, and at run-time to drive the generation process. We assume that answering this question at a higher level of abstraction (task types and abstract gameplays) will allow these relationships to be reused in different declarative knowledge contexts.

This research question (i.e., illustrated in Figure 2) consists of answering more precisely to the following questions: Which kinds of abstract gameplays are suitable for which task types? Is the mapping system-

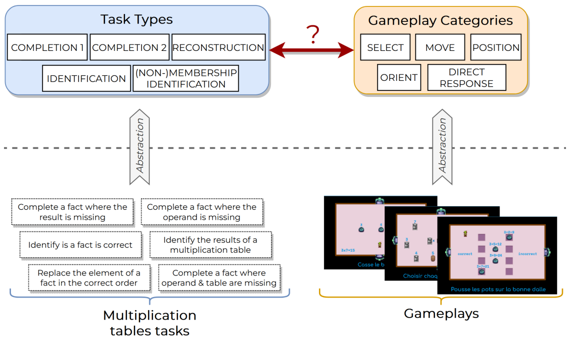


Figure 2: Our Research Question

atic or conditional? If conditional, how to find these conditions?

According to (Tchounikine et al., 2009), this is typically a problem of research in TEL engineering falling into the "*elaborating powerful abstractions*" case where the problem must be addressed from a transdisciplinary perspective.

Previous works have addressed the problem of relationships identification between the educational and game dimensions. The following section aims to position our work in relation to these existing works.

3 RELATED WORK & POSITIONNING

Several existing works have focused on determining the relationships between educational elements and game elements. A pioneer is (Prensky, 2005), who proposed compatible game genres (e.g., action, role-play, adventure) with knowledge to be learned (e.g., facts, skills, judgement, behavior) and learning activities (e.g., questions, experiments, observation). An extension to this work, consisting of adding a relation to the learning styles (i.e., activists, reflectors, theorists, and pragmatists) of (Chong et al., 2005) has been proposed by (Rapeepisarn et al., 2008). Like wise, (Sherry, 2010) defined relationships between some game genres and the 6 levels of Bloom's taxonomy (Bloom, 1956). Similarly, (Gosper and McNeill, 2012) proposed a framework to support the integration of technology in education. This framework defines relationships between learning outcomes (e.g. acquisition of basic facts, automation of skills and concepts), learning processes (e.g. memorization, analogical reasoning, proceduralization), assessment (e.g. self-assessment, peer assessment) and game genres. Although these works are very interesting for the general design of learning games, the identified relationships are not usable at a specification stage for guiding the definition of practical gameplays.

Some work attempts to provide relationships at a specification level. (Dondi and Moretti, 2007) linked learning objectives (e.g., memorization/repetition/ retention), knowledge types (e.g., factual knowledge), and game genres to high-level features that games should possess (e.g., presence of content engine, assessment engine). However, these high-level features do not describe how the relationships are to be implemented in practice.

Other works offer a framework to specify relationships (i.e., either for analyzing existing games or conceiving one). The LM-GM framework (Lim et al., 2013) supports the transition from learning objectives/practices to game elements through a concept called Serious Game Mechanic (SGM). It defines learning mechanics and game mechanics and uses SGM to associate both concepts. However, the presented mechanics are high-level ones (e.g., guidance, collaboration, explore) and the relationships are not meant to be implemented as such. Furthermore, (Hall et al., 2014) proposed a framework to guide the designer in specifying the transition from learning content to core-gameplay. It is composed of 5 categories (i.e., goal, choice, action, rules, feedback) in which a series of questions need to be answered from a real-world and a game-world perspective. However, the framework is more oriented towards the general design of the game rather than its implementation.

In conclusion, existing approaches are more oriented towards defining relationships for analysis purposes or to assist in the high-level design of games rather than specifying relationships for low-level design purposes. Indeed, they address specific learning targets or the contexts of specific game genres, as we do. In our context, we seek to propose an approach to specify relationships between declarative knowledge training tasks and gameplays from the Rogue*lite* genre. These relations need to respect one condition: their specification must allow their implementation.

It is well known that the training and evaluation of declarative knowledge is done through questionnaires/quizzes. Moreover, numerical quizzes, compared to paper ones, allow for user interactions that are closer to the ones we can found into basic training games (for example a multiplication table training games where correct answers make the avatar running faster or jumping to higher platforms). Therefore, using exercises types from quizzes formats as a pivot (i.e., a way to close the gap between task types for declarative knowledge training and gameplay categories) seemed interesting in particular because the use of existing content is a way to reduce subjectivity. Therefore, our work intends to propose a systematic mapping approach based on the use of quizzes exercises types as a pivot. The next sections present the development of our approach, followed by the proposed approach and an application example.

4 APPROACH DESIGN

Several steps were necessary to the elaboration of our mapping approach. At first, we conducted an analysis of quizzes design formats to define the types of existing exercises (i.e., our pivot), after which the following questions appeared: (1) How can we draw a parallel between the types of tasks and the exercises identified? (2) How can we draw a parallel between the gameplay categories and the exercises identified? As previously mentioned, the interactions offered by each quiz exercise are closer to games' interactions. Moreover, every concept (i.e., task types, gameplay categories, and exercises) are characterized by their possible response modalities (e.g., enter one answer, choose between X propositions). Therefore, our second step consisted in using the exercises types to identify possible criteria and parameters in order to specify the task types and gameplay categories and ease the identification of the mappings. The last step consisted in using these parameters *values* (from both task types and gameplay categories perspectives) to compare and identify matches.

4.1 Identification of the Pivot

Foremost, we analyzed the proposed exercises types of 6 formats, mostly extracted from Learning Management Systems (LMS), allowing the creation of numerical questionnaires/quizzes:

- the eponymous and proprietary format from the *itsLearning* (#1) LMS;
- *GIFT* (#2) a markup language for describing tests that is associated to the *Moodle* LMS;
- *Performance Matters Assessment and Analytics* (#3) format associated to the *PowerSchool* LMS;
- *NetQuizzPro* (#4) a software allowing the creation of questionnaire;
- *QTI* (Question & Test Interoperability specification) (#5) from the IMS global learning consortium that defines a standard format to exchange and store assessment content;
- *Tactileo - Maskott* (#6) format associated to the French pedagogical platform of the same name.

This analysis lead us to the definition of 12 different types of exercises useful for declarative knowledge (i.e., only exercises for which the verification of the results can be automatized). Mainly the analysis consisted of a comparison of the exercises in terms of what they allow. Exercises (of different format) that shared the same type of statement, the same number of desired answers and for which the interaction of answers was similar have been merged to compose a single exercise type. Furthermore, some formats combine several exercises into one (i.e., multiple choice and answers were merged in the format of *itsLearning*). In these cases, we considered them to be two independent exercises. Moreover, the possibility of having intruders (i.e., elements not to be associated) was something asked by domain experts, however, none of the "Associate" type of exercise analyzed from the formats offer that possibility. Therefore, it was considered as a possibility in our type of this exercise definition. The final types of exercises defined are:

- Alternative: choosing one answer between 2 options;
- Multiple choice: choosing one answer between X (i.e., $X \geqslant 2$) options;
- Multiple responses: choosing Y (i.e., zero or more) answers between X (i.e., $X \geqslant 2$) options;
- Short answer: enter the correct answer. Multiple form of answers can be accepted, e.g., for example, *How much is 3 times 5?* as two possible answers, which are *15* and *fifteen*;
- Fill-in-the-blanks: enter for each gap of a text the wanted "short" answer;
- Fill-in-the-blanks choices: choose for each gap of a text the correct answer from a list. Each gap can have an associated list of options, or one list can be associated to all gaps;
- Reconstruction: reassemble, in the correct order, each significant element of an information;
- Associate—Group: associate elements from a list or multiple lists together. The association can be done by pairs, or not. The elements can be associated with zero to several other ones;
- Order: replace a set of information in the correct order;
- Graphic choice: point or locate X (i.e., $X \geqslant 1$) elements on a picture.
- Graphic identification: write the correct label for each area-to-complete of a picture;
- Graphic association: associate the correct labels to X areas of a picture.

As a reminder, these types of exercises aim at dealing with declarative knowledge in general, not just multiplication tables. Therefore, some exercises offer a more visual approach that could be useful, for example, in the context of geographical facts. An overview of which format allows for which exercises is presented in Table 1.

Table 1: Exercises by quiz format
(✓ present; ✗ absent; — present but incomplete).

	#1	#2	#3	#4	#5	#6
Alternative	✓	—	—	✗	✗	✗
Multiple Choice	✓	✓	✓	✓	✓	✓
Multiple Resp.	✓	✓	✓	✓	✓	✓
Short Answer	✗	✓	✓	✗	✓	✓
Fill-in	✓	—	✓	✓	✗	✓
Fill-in Choice	✓	—	✗	✓	✓	✓
Reconstruction	✗	✗	✗	✓	✗	✗
Association	—	—	—	—	—	—
Order	✓	✗	✓	✓	✓	✓
G. Choice	—	✗	—	✗	✓	—
G. Identification	✗	✗	✗	✓	✗	✗
G. Association	✗	✗	✗	—	✓	✓

These exercises are characterized by several parameters, such as: their *interactions*, their *response modality* (i.e., input or choice), their *statement type* (i.e., format of the question asked), the *number of answers* desired, and the *number of propositions* presented (i.e., if the response modality of a concrete task of this type is "Choice"). Through our analysis, 6 types of interactions were identified: *Select Y From X* (i.e., the learner must select *Y* answers from a set of *X* values); *Y (Select 1 from* X_1 *to* X_Y*)* (i.e, the learner must make a selection of one answer from each set of proposals); a variant is *Y (Select 1 from X)* (i.e, the learner must select Y answers, one by one, from a set of proposals.); *Write X* (i.e., the learner as to enter X answers); *Order X* (i.e., the learner must order X elements correctly); *Point X* or *Locate X* (i.e., the learner must point X elements on a picture or locate them); *Match Y with X 1-to-1* or *Match Y with X* (i.e., the learner must associate elements from Y with those from X by pairs or not). In addition, 3 types of statement were found: 1) classic statement (i.e., simple text question), 2) graphic statement (i.e., text question accompanied by an image), and 3) To fill-in statement (i.e., question separating textual elements with other types of elements such as answer boxes). Table 2 presents the exercises through their characterization. It is important to note that none of the formats allows for all possible forms of exercise.

4.2 Mapping Task Types to Game Categories

Now that the pivot is specified, the remaining questions are: How to match (1) task types to exercises, and (2) game categories to exercises? The main idea is to use some of the parameters that characterize each concept (i.e. task types, gameplay categories and exercises) to map them.

Task Type to Exercises

Task types are characterized by several parameters, which are: the *number of facts* targeted by the task, the *types of statements* allowed for such a task, the *response modalities*, the *number of desired responses*, and the *number of propositions* presented (i.e., if the response modality of a concrete task of this type is "Choice"). For example, the *Completion 1* type is characterized as follows: one fact is targeted, all statement types are allowed (i.e., classic, graphic and To fill-in), both response modalities can be used (i.e., input and choice), only one response is desired and at least 2 propositions must be presented if the modality equals Choice.

Nevertheless, the assignment of parameter values is not an easy task. At first sight, it could seem possible to carry out a task of the *Completion 2* type through the response modality *Input*. However, presenting a statement in the context of declarative knowledge, such as "$?\times? = 12$", does not give enough information about the fact to work with (i.e., is it 3×4 or 6×2). As another example, for a *Completion 2* task, it is possible to choose one or two answers. This depends on how the choices are presented. If the set of propositions represents numbers, such as [3, 5, 7, 4], two answers must be chosen. However, if each proposition is presented as a multiplication (without the result), such as [3×4; 4×5; 6×3], then only one answer is required. Table 3 presents the task types through their characterization. Thus, except for the *interactions*, task types and exercises are characterized by the same parameters.

Consequently, the mapping consists in comparing the shared parameter's values between task types and exercises. For examples, *Completion 1* corresponds to *Short answer* because the specification of *Short answer*, i.e., $\{$number of facts $=$ 1; type of statement $=$ classic; modality $=$ input; number of desired answers $=$ 1$\}$, is a possible configuration of a concrete task of the type *Completion 1* (i.e., the parameter values are included into those of the type *Completion 1*). This gives questions such as "What times 5 equals 15?" and "What does 3 times 5 equal?". *Completion 1* also corresponds to *Fill-in-the-blanks choices*

Table 2: Characterization of the exercises.

	Number of Facts	Statement Types	Response Modality	Number Answers	Number of Choices	Interactions
Alternative	1	Classic	Choice	1	2	*Select 1 from 2*
Multiple Choice	1	Classic	Choice	1	2 to ∞	*Select 1 from X*
Multiple Resp.	1	Classic	Choice	0 to ∞	2 to ∞	*Select Y from X*
Short Answer	1	Classic	Input	1	0	*Write 1*
Fill-in	1	To fill-in	Input	1 to ∞	0	*Write Y*
Fill-in Choice	1	To fill-in	Choice	1 to ∞	2 to ∞	*Y (Select 1 from X)* *Y (Select 1 from* X_1 *to* X_Y*)*
Reconstruction	1	To fill-in	Choice	2 to ∞	2 to ∞	*Match Y with X 1-to-1*
Association	2 to ∞	Classic	Choice	2 to ∞	4 to ∞	*Match Y with X 1-to-1* *Match Y with X*
Order	2 to ∞	Classic Graphic	Choice	1 to ∞	2 to ∞	*Order Y*
G. Choice	1 to ∞	Graphic	Choice	1 to ∞	2 to ∞	*Point Y* or *Locate Y*
G. Identification	1 to ∞	Graphic	Input	1 to ∞	0	*Write Y*
G. Association	1 to ∞	Graphic	Choice	1 to ∞	1 to ∞	*Match Y with X 1-to-1*

Table 3: Characterization of the task types.

	Number of Facts	Statement Types	Response Modality	Number Answers	Number of Choices
Completion 1	1	Classic Graphic To fill-in	Input Choice	1	0 2 to ∞
Completion 2	1	Classic Graphic To fill-in	Choice	1 or 2	2 to ∞
Reconstruction	1	Graphic To fill-in	Choice	2 to ∞	2 to ∞
Identification	1 to ∞	Classic	Input Choice	1 to ∞	0 2 to ∞
(Non-)Membership Identification	1 to ∞	Classic Graphic	Input Choice	2 to ∞	0 2 to ∞

exercise specified as {number of facts = 1; type of statement = to fill-in; modality = choice; number of desired answers = $[1-\infty]$; number of choices = $[2-\infty]$}. This gives questions such as "__ times 5 equals 15".

Thanks to these mappings, each task type can also be described by its possible interactions (i.e., the interactions of the exercises corresponding to the task type considering the number of requested answers). As an example, the *Short answer* exercise type asks the learner to write down one short answer to a textual question. Thus, its interaction parameter as for value *Write 1*. A task of the *Completion 1* type could ask questions such as "What does 3 times 5 equal?", leaving the learner to write down *15*. Therefore, *Completion 1* has *Write 1* for possible interaction. As a result of all mappings, *Completion 1* can be achieved through the following interactions: *Select 1 from X* (i.e., $X \in [2, \infty]$), *Write Y* (i.e., Y is the number of wanted answer therefore $Y = 1$), *Y (Select 1 from X)*, *Point Y* or *Locate Y*, *Match Y with X 1-to-1*.

Gameplay categories to Exercises

Each game category represents gameplays that are similar in terms of the actions to be performed, such as opening the right chest, choosing the right pot, passing through the right bridge which belong to the *SELECT* category. Therefore, the common parameters of these gameplays (e.g., number of facts interrogated, number of possible answers) represent those of the category itself.

After analysis, we characterized these categories by the following parameters: the *interactions*, the *response modality* (i.e., input or choice), the *statement type* (i.e., format of the question asked), the *number of* *facts* targeted, the *number of answers* desired, and the *number of propositions* presented (i.e., if the response modality of a concrete task of this type is "Choice"). These parameters are quite similar to those used for the exercises. They represent a minimal and relevant set of parameters that allow us to discriminate the different categories and gameplays. As an example, the *SELECT* category is characterized as follows: 1 to many facts can be targeted, both classic and to fill-in statement types are allowed, choice is the only possible response modality, 1 to many answers can be desired, and two interactions (i.e., *Select Y from X*, and *Y (Select 1 from* X_1 *to* X_Y*)*) are possible.

However, during the characterization phase, we realized that the possible interactions and the type of statement changed depending on whether one or more responses were desired. Therefore, in order to simplify the mappings, each category allowing one to multiple possible responses was divided into two subcategories: single (i.e., only one possible response) and multiple (i.e., 2 to many possible responses).

As a result, our 5 categories turned into 9. Table 4 presents the gameplay categories through their characterization. Afterwards, the mapping consisted in directly comparing the parameter's values.

Task Type to Gameplay Categories

From there, we disposed of all the necessary information to answer our main question: Which task type are suitable for which gameplay categories? What are the conditions?

The final step consisted in comparing the task types and categories on the basis of their parameter values (i.e. comparing Table 3 with Table 4). During that step, we observed that 2 parameters represented mapping conditions based on their values: the type of statement and the response modality. Therefore, the obtained relationships are quadruplet composed as follows: (<task type>, <statement type>, <response modality>, (<category1>, <category2>, ...)). Each task type can have from 1 to 6 associated relationships.

In conclusion, this section has presented the process followed to map the task types for declarative knowledge training to gameplay categories for the Roguelite video game genre. The next section will present the results obtained.

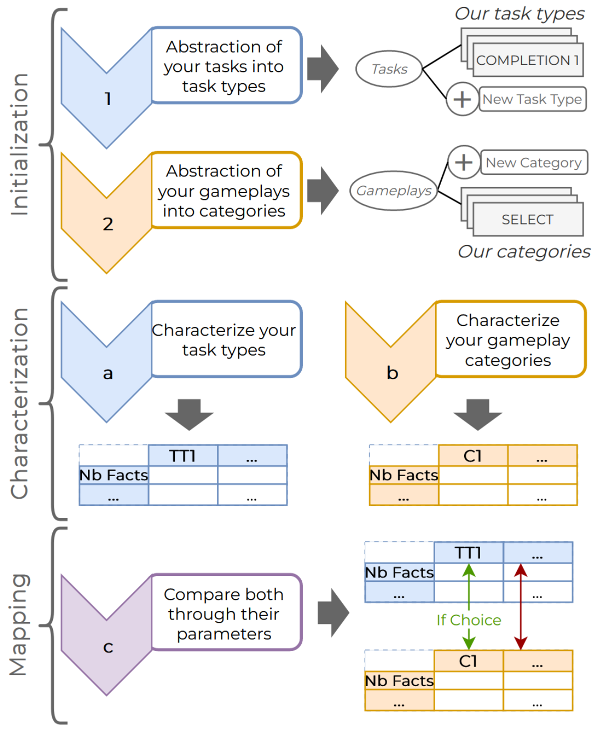


Figure 3: Proposed Mapping Approach.

5 RESULTS

The presented work led to two contributions: (1) an approach to map designers' own task types to their own categories of gameplays, and (2) mappings between our own task types with our gameplay categories.

5.1 A Mapping Approach

Our proposal consists of a two to five-steps approach, illustrated in Figure 3. The initial steps are to:

1. abstract the concrete tasks by using the types of tasks presented (e.g. a task "associate the right date with the historical event" becomes complete a fact with a missing element) or by creating new task types;
2. associate the gameplay to one of the categories presented or to a new category.

From here, four states are possible: new task types and categories have been created, only new task types have been created, only new gameplay categories have been created, or nothing has been created. Depending on the condition, the instructions below must be followed:

1. If new task types and new gameplay categories were created:

Table 4: Characterization of the gameplay categories ((S) = Single; (M) = Multiple).

<table>
<tr><th></th><th>Number of Facts</th><th>Statement Types</th><th>Response Modality</th><th>Number Answers</th><th>Number of Choices</th><th>Interactions</th></tr>
<tr><td>SELECT (S)</td><td>1</td><td>Classic
To fill-in</td><td>Choice</td><td>1</td><td>2 to ∞</td><td>Select 1 from X</td></tr>
<tr><td>SELECT (M)</td><td>1 to ∞</td><td>Classic
To fill-in</td><td>Choice</td><td>2 to ∞</td><td>2 to ∞</td><td>Select Y from X
Y (Select 1 from X_1 to X_Y)</td></tr>
<tr><td>MOVE (S)</td><td>1</td><td>Classic
Graphic
To fill-in</td><td>Choice</td><td>1</td><td>2 to ∞</td><td>Select 1 from X
Point 1 or Locate 1
Match 1 with 1</td></tr>
<tr><td>MOVE (M)</td><td>1 to ∞</td><td>Classic
Graphic
To fill-in</td><td>Choice</td><td>2 to ∞</td><td>2 to ∞</td><td>Match Y with X
Point Y or Locate Y
Select Y from X
Y (Select 1 from X_1 to X_Y)</td></tr>
<tr><td>ORIENT (S)</td><td>1</td><td>Classic
To fill-in</td><td>Choice</td><td>1</td><td>2 to ∞</td><td>Select 1 from X</td></tr>
<tr><td>ORIENT (M)</td><td>1 to ∞</td><td>Classic
To fill-in</td><td>Choice</td><td>2 to ∞</td><td>2 to ∞</td><td>Y (Select 1 from X_1 to X_Y)
Y (Select 1 from X)</td></tr>
<tr><td rowspan="2">POSITION (S)</td><td rowspan="2">1</td><td>To fill-in</td><td rowspan="2">1</td><td>Input</td><td>0</td><td rowspan="2">Select 1 from X
Point 1 or Locate 1</td></tr>
<tr><td>Classic
Graphic</td><td>Choice</td><td>2 to ∞</td></tr>
<tr><td>POSITION (M)</td><td>1</td><td>Graphic</td><td>Input</td><td>2 to ∞</td><td>0</td><td>Write Y</td></tr>
<tr><td>DIRECT RESP.</td><td>1</td><td>Classic</td><td>Input</td><td>1</td><td>0</td><td>Write 1</td></tr>
</table>

(a) The first step is to characterize the task types using the six parameters defined above (i.e., number of facts, types of statements, response modalities, number of desired responses, number of propositions, and interactions). In a sub-step, the mapping between task types and quiz exercises (see Table 2) must be done to define the values of the *interactions* parameter.

(b) The second step is to characterize the gameplay categories using the same parameters.

(c) Finally, the last step is to compare both tables (i.e., characterization) through their values. As a reminder, the values of the *Statement Type* and the *Response Modality* parameters are possible conditions of the relations.

2. If only new task types were created, then realize step 1a and step 1c.
3. If only new gameplay categories were created, then realize step 1b and step 1c.
4. If no new elements have been created, the work is already done, cf. Figure 4.

Let's take as example a task type **T1** characterizes as such {number of facts = 1; type of statement = classic; modality = input or choice; number of desired answers = 1}, and a gameplay category **C1** = {number of facts = $[1-\infty]$; type of statement = classic or to fill-in; modality = choice; number of desired answers = $[1-\infty]$}. In this case, only one relationship would result: *(**T1**, Classic, Choice, **C1**)*.

5.2 Resulting Mappings

As a result of the process presented in section 3, several conditional relationships were identified between each task type and the gameplay categories.

These relationships are presented in Figure 4. If the categories do not have (S) or (M), it means that both are present.

For example, the task type *Identification* has two relationships: *(Identification, Classic, Input, (Position (S), DIRECT RESPONSE))* and *(Identification, Classic, Choice, (SELECTION (S,M), MOVE (S,M), ORIENT (S,M))*.

6 DISCUSSION & FURTHER WORK

This section discusses the limitations of our work, presents an experiment to validate some mappings, and outlines a way to model the identified relationships.

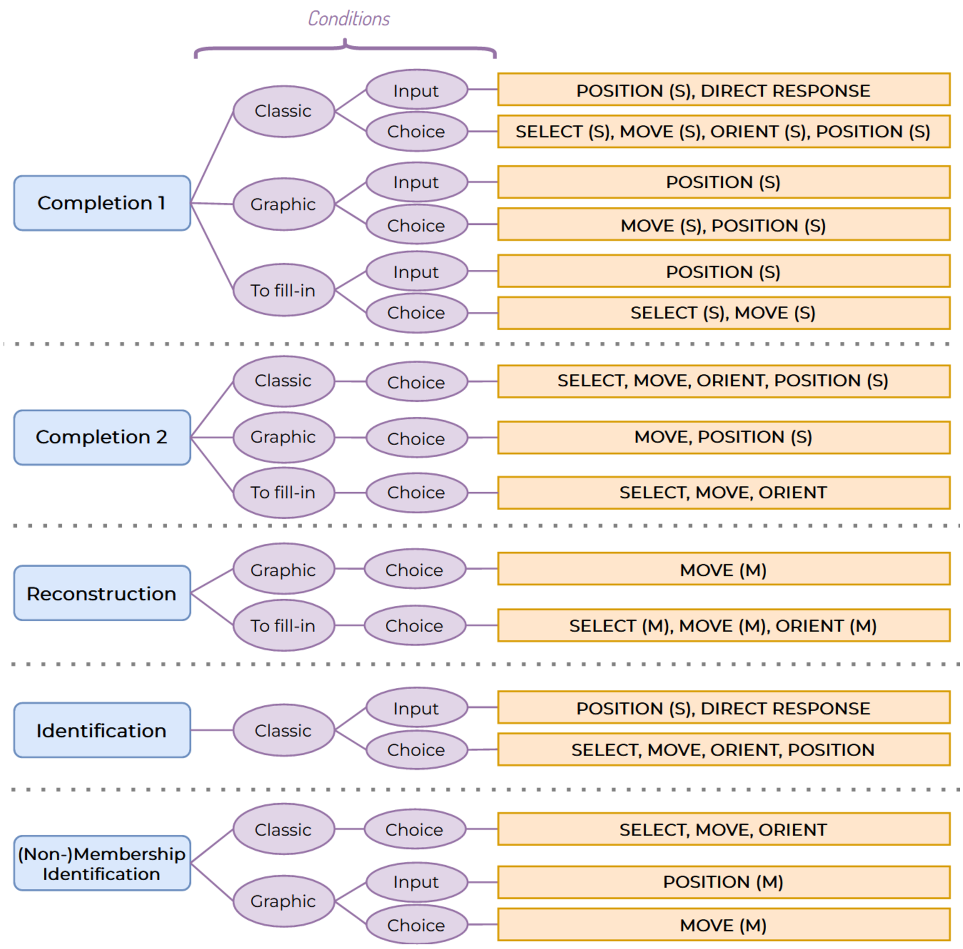


Figure 4: Conditional relations between task types and gameplay categories.

6.1 Extension of the resulting mappings and genericity

Our approach revealed some limits. First, due to the non-exhaustiveness of our task types, all possible exercise types are not covered (i.e., this is the case of *Order*). It is mainly due to our method: we intended to start with a very first domain context while abstracting tasks types and gameplay categories. It is a very first step towards proposing a complete domain-independent and generic approach.

Consequently, other domains than multiplication tables have to be considered to cover, and refine if necessary, our proposal. It is also possible that the current task types have to be modified or extended to cover all exercise types. In particular, we are currently studying a second domain, consisting in the history and geography declarative knowledge necessary to obtain the French diploma "*Diplôme National du Brevet*" (present in the 9th grade).

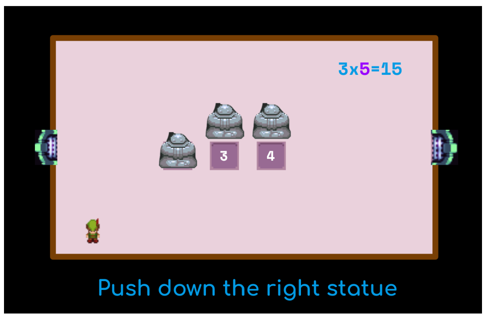


Figure 5: Second solution example.

6.2 Validation of the mappings

In order to gather feedbacks on the gameplay mock-ups (i.e., to identify relevant gameplays and game elements), we proposed to the members ($\approx$ 10 persons) of the user group (of the project AdapTABLES) a survey presenting possible gameplays for each type of task. This experimentation was also an opportunity to validate some mappings (i.e., the relations for which the categories have existing gameplay mock-ups). As the experiment is situated in the context of multiplication tables, none of the mappings with the condition "Graphic" are evaluated here. However, since mock-ups of each compatible categories for each task types were created, other mappings are evaluated here. Let's take the example of a gameplay consisting in selecting the right pot among several pots bearing propositions (i.e., *SELECT* with Choice) to answer a textual question of the type "$3\times? = 15$" (i.e., *Completion 1*). If this gameplay is validated by the survey, then so is the relationship *(Completion 1, Classic, Choice, SELECT)*.

According to the first results, the **mappings presented seem relevant**. Negative comments are generally related to the lack of precision of some information or to didactic problems. For example, MOVE-type gameplays requiring objects to be placed in the correct answer areas were rejected because the objects would hide the answers, thus impacting learners' thinking. The issue is not related to the mechanics (i.e., moving objects to predefined areas), but a cognitive one that can be corrected. A basic solution would be to display the value above the selected object. An alternative would be to display the chosen value in the statement at the right position using a different color. Figure 5 illustrates the latter solution: the statue pushed on the left tile hides the associated '5' value, but this value appears now in purple in the room's statement.

Furthermore, the mock-ups of the ORIENT game have received mixed reviews. This is due to the fact that the object chosen to be oriented (i.e., directing the light of a streetlamp) lacks cognitive meaning. Therefore, other mock-ups should be proposed to properly assess the relationships associated with the ORIENT category.

6.3 Modelling the mappings

As mentioned earlier, our overall goal is to build a generator of Rogue*lite* oriented learning game activities for declarative knowledge training.

The originality of our overall work is the use of Model-Driven Engineering (MDE) (Kent, 2002) tools and principles to design the generator. The idea is to specify all the information (domain-dependent tasks, task types, game categories, gameplays, game elements and relationships) in different, interconnected models that are consistent with a dedicated metamodel that we are also specifying. Therefore, each generation could be considered as a model transformation according to MDE.

Figure 6 proposes a first insight of the part of this metamodel focusing on the mapping structure defined in this article. The resulting mappings will be specified as a model in conformance with this metamodel extract. The domain-dependant tasks, as well as the specification of the concrete gameplays, and their implementations into game elements, are not depicted in the figure. As an overview of the mapping process followed at runtime, here are the main steps starting from a given identified domain-dependent task:

1. get the associated task type;
2. collect all relations from the mapping model that are related to this task type;
3. restrict the collected relations to those whose associated condition is satisfied by comparing the statement and modality values of the condition to those of the original task;
4. collect the gameplay categories of the remaining relations.

The generation algorithm will then handle further steps such as selecting the gameplays implementing these game categories, filtering them according to other information (e.g. which gameplays are unlocked and available for this learner-player), instantiating the game elements composing the chosen gameplay, etc.

7 CONCLUSION

To conclude, this paper introduced an approach to map task types for declarative knowledge training to Rogue*lite* oriented gameplay categories. The originality of this work lies on two points. Firstly, the proposed approach is based on the use of a pivot (i.e., exercises in the form of questionnaires). Secondly, it is oriented towards automating the design of learning game activities (i.e., generation) and therefore specifies fine-grained relationships.

In the future, we plan to: (1) continue the analysis of the second application domain in order to have generic task types with declarative knowledge; (2) focus on specifying gameplays in terms of game elements; and (3) model relationships (and other concepts) to implement a first version of the generator.

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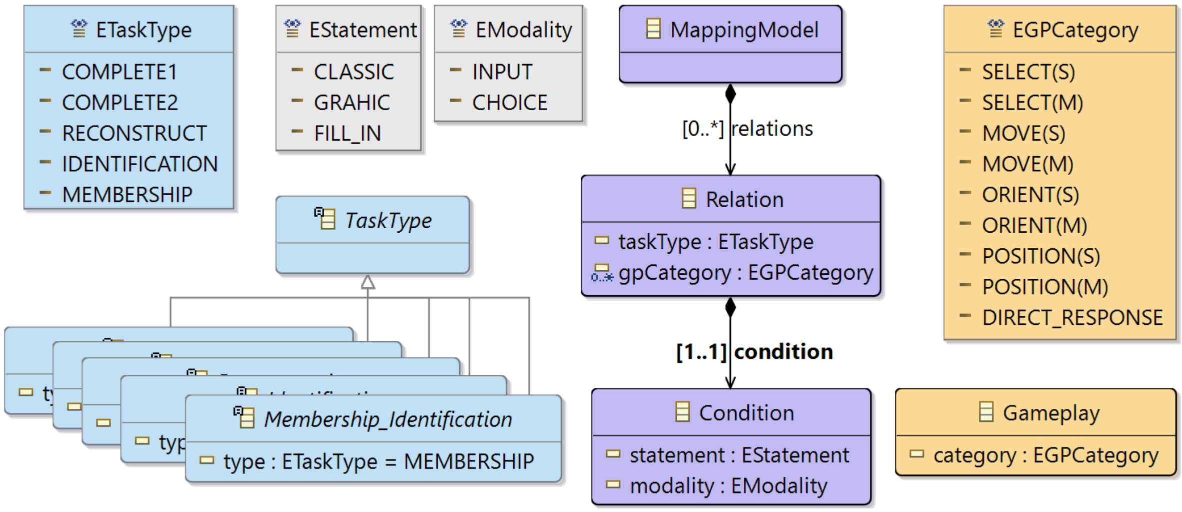

Figure 6: Example of EMF Ecore Modelling for relationships, task types and gameplays.

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