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# Player perceptions of informal learning in non-educational games

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**Abstract:** The potential of non-educational games in learning is well-established, but there have been relatively few empirical studies attempting to explore the kinds of informal learning that take place in non-educational games outside of formal education. Simultaneously, student motivation is known to have a connection to learning outcomes, but there is a lack of research on the relationship between gaming motivations and informal learning in games. This paper aims to fill the gap in research by, firstly, forming an empirically-based understanding of what players perceive they are learning from playing non-educational games, and secondly, exploring the potential connections of self-articulated learning outcomes with motivations to play games and preferences for gameplay activities. The research data was collected through an online survey panel. The respondents were asked to describe in open-text answers what they had learned by playing games, and their motives and gameplay activity preferences were measured using two psychometric instruments, Motives of the Autonomous Player, MAP (Vahlo and Tuuri, submitted) and the gameplay activity inventory GAIN (Vahlo et al, 2018). The open-text responses analysed using data-driven content analysis, which resulted in 11 main categories of learning outcomes. Cluster analysis of the main categories revealed three clusters indicating informal game-based learner types: (1) Learning perseverance, learning mainly related to coping skills and self-enhancement, (2) Learning practices and communalities, focusing on practical and interpersonal skills, and (3) Learning to perform, emphasising cognitive and sensori-motor competencies. Comparisons of the learning outcome clusters with motives and gameplay preferences revealed the learner types had distinct profiles which denote differences between learner types in the overall motivation to play games, in certain motivational factors, and in preferences of gameplay activities. Based on this analysis we suggest the existence of two distinct continuums, transfer of learning, and the situational dependence to gameplay activities, where these learner types are located.

**Keywords:** informal learning, learner types, non-educational games, learning outcomes, gameplay motives, gameplay preferences

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## 1. Introduction

Unlike the purposeful activities that individuals and communities do, play does not seem to have an obvious goal. Play appears to epitomise humans' desire to act on a purely voluntary basis – often just for fun. However, this is not to say that play would not have any benefits. From the developmental and evolutionary perspectives, human play and games have functioned as crucial forms of learning (e.g., Bruner et al, 1976). For children, playing might be just a fun activity, but at the same time, children develop physical or social skills that are relevant in their future (Piaget, 1962[1951]). Furthermore, it is intriguing to consider play as an activity that satisfies basic human needs of self-determination, especially in terms of fulfilling the desire to experience autonomy (Deci and Ryan, 2012). Thus, it is worthy of further exploration to consider the 'autonomous player'.

Non-educational games is a term used in the context of game-based learning to describe games designed for entertainment as opposed to educational games which are designed for learning. Our focus is on informal, spontaneous learning occurring by voluntarily playing non-educational games. In this millennium, informal learning has also become an area of interest for educational policy makers in the European Union as a method of lifelong learning, which has been considered as a solution for the needs of the European labour market (Tuschling & Engemann, 2006; Panitsides & Anastasiadou, 2015). Informal learning, where learning takes place even when it is not the main objective of an activity, is an integral part of modern video game design, as games are designed to teach their players how to play them (cf. Gee, 2003; Poretski and Tang, 2022). However, we are interested in the diversity of informal learning taking place when playing non-educational games. Instead of asking how games can be used in teaching, we study the perceived learning outcomes of playing games. In this study, this is essentially done in an open-ended manner, giving people the opportunity to describe what they have learned without presenting them with any presuppositions. The main goal of this study is to form an empirically based understanding of what players perceive they are learning from non-educational games, and how they conceptualise learning in self-report studies.

Due to the close relationship of play and learning, it is tempting to consider the possibility of similarities between the motives of an autonomous player and the learning outcomes yielded by gameplay. Student motivation is known to have a connection to learning outcomes (e.g. Janosz, 2012), but there is a lack of research on the

relationship between gaming motivations and informal learning in games. The secondary goal of this study is to investigate, do motives and learning outcomes together form observable patterns. This question is addressed using a psychometric, validated instrument, MAP, that measures motive dimensions of autonomous gaming (Vahlo and Tuuri, submitted). Furthermore, using the gameplay activity inventory GAIN (Vahlo et al, 2018), we study player preferences of particular types of gameplay activities and investigate their possible associations with perceived learning outcomes.

First, we address existing research in learning from non-educational games. Then we introduce the data and qualitative analysis methods. The results are presented in three sections: qualitative analysis and formulating learning outcome categories, cluster analysis of the data, and statistical analysis of the connections of learning outcome clusters with MAP and GAIN respectively. This is followed by discussion and conclusions.

## **2. Informal learning from games**

Non-educational games, despite their name, have been frequently used for educational purposes (Squire, 2003; Egenfeldt-Nielsen, 2006; Wastiau et al, 2009). Research on the use of commercial off-the-shelf games in education has identified their potential in learning skills such as dealing with depression (Olson, 2016), teamwork and other social skills (Sherry, 2016; Silva et al, 2021), attention abilities (Franceschini et al, 2013), and enhancing cognitive performance (Dale and Green, 2016). Furthermore, non-educational games have been used in teaching a variety of subjects such as languages (Chen and Yang, 2012; Reinders, 2012), history (Squire 2005), and science (de Aldama and Pozo, 2020). Majority of this previous research on learning from games has studied learning outcomes using skill-testing or other forms of formal learning assessment.

There have been surprisingly few empirical studies tackling the question of what kinds of informal learning take place while playing and how players themselves perceive their learning (Gee, 2003; Iacovides et al, 2014; Matijević and Topolovčan, 2019). This research aims to take a more comprehensive approach by mapping out the variety of informal learning taking place in non-educational games.

## **3. Data and qualitative methods**

The data (n=1202) for this study was collected via Prolific, a crowdsourcing platform that holds an online panel in multiple countries. Using online panels in survey research has been found particularly appropriate for explorative research such as the one reported here (Lehdonvirta et al, 2020). The survey was targeted at adult (ages 18-70) UK or USA residents who reported playing videogames at least occasionally. We asked the respondents to describe in their own words what they had learned by playing games and 95.2% (1145) answered this voluntary question.

We used qualitative data-driven content analysis to form categories of self-identified learning outcomes from these responses. After excluding the responses not answering the question, there were 1046 responses (86.9% of the whole data) which discussed learning outcomes. Each response was read and placed into one or more categories, which were created as the analysis advanced. This meant that the data had to be reread several times in order to include the new categories. However, while aiming for an open-ended approach to analysis, the categorization was undoubtedly influenced by the researcher's previous conceptual models related to learning. In the next stage of the analysis, based on joint review by all authors similar categories were further grouped under different main categories turning the initial categories into subcategories.

## **4. Results**

### **4.1 Learning outcomes**

Our analysis identified 117 different subcategories of learning. These included categories with only one or two responses but in the most common categories there were more than 100 responses ('problem solving', 'language skills', 'hand-eye coordination'). The subcategories were grouped into 11 main categories, which represent a wide variety of learning in terms of their contents. A single response was typically placed into one (32.1% of responses) or two (30.6%) categories of learning outcomes, but the maximum number of categories for a response was 13. Next, we will explicate the main categories (Table 1).

**Table 1:** Learning outcome main categories

Main category	Responses (f)	Responses (%)
Learning to play	111	9.2%
Learning about games	37	3.1%
Learning about self	101	8.4%
Thinking skills	651	54.2%
Interpersonal skills	294	24.5%
Embodied behaviors	301	25.0%
Subject matter	276	23.0%
Practical skills	281	23.4%
Coping skills	185	15.4%
Self-enhancement	170	14.1%
Learning to learn	18	1.5%

*Learning to play.* This main category included respondents reporting that playing games had taught them to play those particular games. Some of the responses in this category were laced with scepticism towards the possibility of learning anything from games, as in the following quotation.

*I do not think I have learned anything from video games, apart from how to play the game in question. I think they are too limited and abstracted to be of any use in real life.*

In addition, *learning to play* included learning to play games in general, learning to play games of a particular genre, such as FPS (first person shooter), or evolving in particular game techniques like aiming or puzzle-solving. In the following example, learning to play is described as becoming familiar with conventions of game design.

*I learned that if you are meeting enemies then you are going the right way.*

*Learning about games.* Self-articulated learning outcomes also reached to game cultures more broadly. This meant learning about the fictional game worlds but particularly about game communities, their composition (“many of the gamers are older than I expected”), and communication. This included insights into game culture phenomena, such as ‘toxic’ behaviours or online identities, the latter reflected in the following.

*I've learned that people like to portray things within the games that they cannot in real life. They can be almost anything they want to be or do anything they want to do in a virtual world.*

*Learning about self.* Related to *learning about games* is also the subcategory of learning about one’s own gaming preferences such as liking certain genres or preferring single-player or multiplayer games. However, this subcategory shares more similarities with those related to self-discovery. The following response portrays the intertwining of an increased understanding of personal game preferences (playing alone) and learning about self more broadly (wanting to achieve things by themselves).

*I like playing skill games and it made me realize I like to play alone and achieve things on my own.*

*Thinking skills.* This was the most common main category emerging from the analysis. Problem-solving was the most common subcategory of thinking skills and one of two most common learning outcomes in the data. Other prominent learning outcomes from this main category were planning, strategizing, management skills, critical thinking, and creativity.

*I have learned how to keep better track of time and how to strategize when I do things throughout my life.*

*Interpersonal skills.* Collaborating and cooperating with others was mentioned often in the responses, along with communication skills. Learning interpersonal skills were sometimes situated in particular social contexts. Respondents described learning online communication, or learning “to interact with people in a competitive setting”. Another common interpersonal skill was an increased understanding of how to form relationships.

*I have learned how to build team friendships and motivating fellow players.*

*Embodied behaviours.* Hand-eye coordination, muscle memory, reaction time, and dexterity were among the most common embodied behaviours in the data. Mentions of these are straightforward, like this one: “I have learned better hand-eye coordination and finger dexterity.” Other subcategories are memory, spatial awareness and pattern recognition. Interestingly, this main category also includes mentions of purposefully using games to improve certain skills.

*Playing video games helped my eye/hand coordination after having surgery on my hand.*

*Subject matter.* Several respondents recounted learning about particular subject areas, such as history, geography, other cultures, mathematics, and science, while some mentioned even more particular subjects like cars, weapons or sports.

*I have learned more about the rules of sports when playing games like Fifa.*

Respondents often specified they now had improved their knowledge on a certain topic, while some described it as learning “facts” or “trivia”.

*Practical skills.* Learning new languages or developing existing language skills was one of the two most common learning outcomes. There were also mentions of several technical skills, from learning to efficiently use a computer keyboard to advanced skills such as coding. The variety of skills extended from storytelling to business skills. Some mentioned applying these practical skills to real-life situations, as in the following.

*I now have a much firmer grasp of how maps translate into real world environments.*

*Coping skills.* The most common coping skill emerging from the data was perseverance, often described vividly as by one respondent narrating, they had learned to “try again and again until I find the right combinations to win”. Several respondents mentioned learning skills pertaining to self-regulation, such as controlling their emotions or behaviour, or managing stress.

*I've learned that playing video games is a great way to relieve stress and escape from your problems for a bit if you need to do so.*

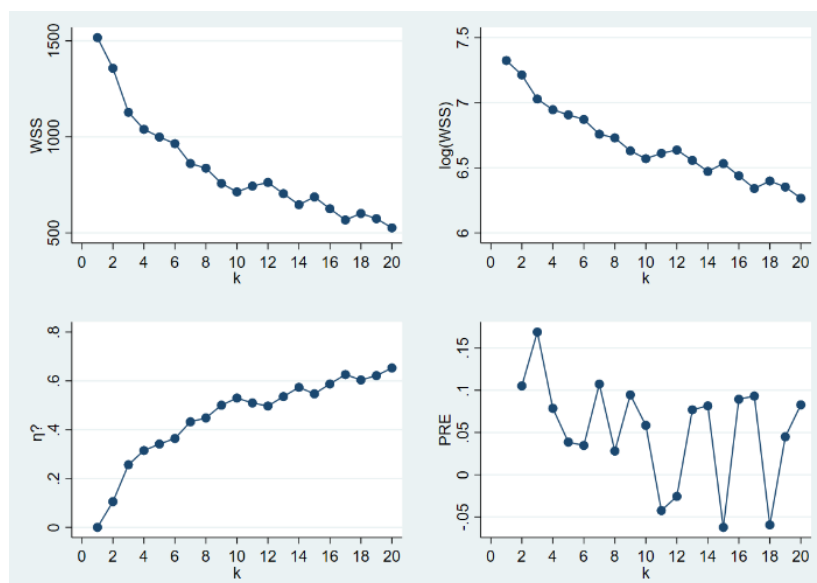
*Self-enhancement.* Several learning outcomes in the data were related to attitudes or personality traits, like determination, and flexibility. One respondent described learning “[h]ow to be more patient, how to not rush at things and take your time to make the right moves”. Indeed, patience was the most common learning outcome in this main category. Another interesting subcategory was ‘confidence’ as exemplified in responses such as “[playing] helps to reassure that I'm still skilled at something”.

*Learning to learn.* A small but noteworthy category among the learning outcomes was learning to learn. Some responses described particular learning techniques such as ‘note-taking’ or ‘researching strategies’.

#### **4.2 A Cluster Analysis on Informal Game-Based Learners**

We proceeded to explore what kinds of groups could be identified from the survey respondents based on their self-articulated responses. Based on the results of the qualitative content analysis, we constructed eleven binary dummy variables for each survey participant. Value 0 or 1 was then assigned for participants for each variable based on whether they had described the learning main category or not in their open-ended responses, not depending on whether they had mentioned one or more of its subcategories.

An exploratory cluster analysis with Stata 16.2 software was conducted to investigate how main categories of learning outcomes were associated with each other on the level of the survey participants in order to identify learner types in the context of informal learning from games. We began the clustering procedure by examining the data to identify the optimal number of clusters that ought to be extracted. This was done by searching for kinks in the scree plots that were generated from the within sum of squared (WSS) or its logarithm [log(WSS)] for all possible cluster solutions between 2 and 20 clusters (Makles, 2012; Figure 1). As both WSS and log (WSS) clearly suggested a solution of three learner types, we decided to construct three learner clusters.



**Figure 1:** Scree plots for identifying the correct number of clusters, based on which a 3-cluster solution was selected

We then conducted an unsupervised K-Means clustering for a three-cluster solution using the Jaccard index. K-Means is a partition cluster analysis method which groups observations into a number of clusters that do not overlap. The Jaccard procedure calculates binary similarity coefficients based on proportion of matches when the value of each included variable is 1. In other words, the three clusters (Table 2) were formed based on co-occurrences of the main categories of learning outcomes in the data. The whole survey sample of 1,202 respondents were included in the cluster analysis.

**Table 2:** The three clusters of informal game-based learners, their cluster sizes and proportions in the learning outcome main categories

	Cluster 1 Learning perseverance	Cluster 2 Learning practices and communalities	Cluster 3 Learning to perform
N	323	278	601
Learning to play	2.2%	5.4%	13.5%
Learning about games	1.2%	3.2%	3.8%
Learning about self	1.9%	6.1%	11.3%
Thinking skills	0.0%	5.0%	72.7%
Interpersonal skills	0.0%	55.4%	13.6%
Embodied behaviours	0.3%	15.8%	31.8%
Subject matter	15.5%	21.2%	14.1%
Practical skills	0.0%	59.7%	11.6%
Coping skills	24.1%	8.3%	9.3%
Self-enhancement	17.6%	11.2%	11.3%
Learning to learn	1.9%	1.1%	1.5%

Apart from the main category of *Subject matter*, which is relatively equally distributed across the clusters, the three resulting clusters seem to represent clearly distinctive types of learning outcomes (Table 2). (1) The first cluster appears to denote learning outcomes relating to learners themselves and especially to the development of patience and perseverance in overcoming the challenges of life ( *coping skills, self-enhancement*). (2) For the second cluster, the learning outcome main categories that differentiate it from the other two emphasise practical everyday skills that are often embedded in social communities (*practical skills, interpersonal skills*). (3) The third cluster appears to represent performance-oriented cognitive and sensori-motor competence (*thinking skills, embodied behaviours*) that most closely seem related to the gameplay-situated, strategical, logical and embodied skills needed for performing well in a game.

#### 4.3 Player Motivations and Preferences

Next, we investigated how the identified learner types were associated with prevalent motives to play videogames, that is, if and how motives related to e.g. competition, autonomy, or social interaction were linked with one or more of the three learner clusters. This was done by applying the Motives of the Autonomous Player (MAP) inventory, which is a recent nine-factor model of gameplay motives that is currently being validated. We furthermore applied a psychometric instrument to study if types of gameplay appreciation was related to the clusters. This was studied by making use of the five-factor gameplay activity inventory (GAIN).

Cronbach’s alphas (95% confidence intervals for the alphas) for each of the MAP and GAIN factors were calculated for the sample, and these are reported below in the brackets:

MAP is a 34-item inventory (Vahlo and Tuuri, submitted) that assesses nine prevalent and general motives to play videogames: *Immersive agency* ( $\alpha=0.83$ , 95% CI: 0.81-0.84), *Competitive mastery* ( $\alpha=0.84$ , 95% CI: 0.82 to 0.85), *Affective engagement* ( $\alpha=0.86$ , 95% CI: 0.84 to 0.87), *Nostalgia* ( $\alpha=0.88$ , 95% CI: 0.87 to 0.89), *Utility* ( $\alpha=0.86$ , 95% CI: 0.85 to 0.87), *Social* ( $\alpha=0.90$ , 95% CI: 0.89 to 0.91), *Addiction* ( $\alpha=0.87$ , 95% CI: 0.86 to 0.89), *Escapism* ( $\alpha=0.84$ , 95% CI: 0.82 to 0.85), and *Boredom* ( $\alpha=0.76$ , 95% CI: 0.74 to 0.78).

GAIN is a 15-item instrument (Vahlo et al, 2018) for studying players’ preferences in distinctive types of gameplay activities. In short, the instrument assesses what kind of player engagement is attractive for players, when engagement is understood as participating in gameplay through *Aggressive*  $\alpha=0.83$  (CI 0.82 to 0.85), *Explorative*  $\alpha=0.75$  (CI 0.72 to 0.77), *Coordinative*  $\alpha=0.65$  (CI 0.61 to 0.68), *Caretaking*  $\alpha=0.73$  (CI 0.70 to 0.76), or *Managing*  $\alpha=0.65$  (CI 0.62 to 0.68) modes of interaction.

As a next step in analysis, sum variables and standard deviations were generated and calculated for the nine-factor MAP and five-factor GAIN constructs, as well as all of their factors for the three learner clusters (Table 3). We calculated one-way analyses of variance (ANOVAs) between the three clusters for motive and gameplay activity factors to identify if there were statistically significant differences between the group means.

**Table 3:** Motive and gameplay activity type factor-level mean sums as well as average motive and gameplay activity sums across all factors for the three learner clusters. One-way analyses of variance (ANOVAs) between the cluster means: \*p < 0.05, \*\* p < 0.01, and \*\*\* p<0.001

	Cluster 1 Learning perseverance (N=323)		Cluster 2 Learning practices and communalities (N=278)		Cluster 3 Learning to perform (N=601)		Model
	Mean	SD	Mean	SD	Mean	SD	
Immersive Agency***	3.77	1.27	4.37	1.24	4.11	1.27	MAP
Competitive Mastery***	3.54	1.31	4.01	1.38	3.89	1.30	MAP
Affective Engagement***	5.58	1.03	5.97	0.88	5.84	0.86	MAP
Nostalgia***	3.89	1.50	4.42	1.46	4.31	1.47	MAP
Utility***	3.62	1.51	4.18	1.50	4.11	1.49	MAP
Social***	3.70	1.58	4.64	1.57	4.12	1.62	MAP
Addiction	2.43	1.23	2.65	1.31	2.50	1.37	MAP
Escapism**	5.11	1.24	5.46	1.27	5.27	1.07	MAP

	Cluster 1 Learning perseverance (N=323)	Learning practices and communalities (N=278)	Cluster 2 Learning practices and communalities (N=278)	Cluster 3 Learning to perform (N=601)	Model		
Boredom	4.81	1.34	4.80	1.39	4.83	1.27	MAP
Aggression***	4.19	1.58	4.69	1.49	4.48	1.61	GAIN
Caretaking	4.29	1.26	4.49	1.36	4.38	1.31	GAIN
Coordinate	4.33	1.30	4.33	1.35	4.40	1.25	GAIN
Management	4.45	1.17	4.66	1.17	4.60	1.17	GAIN
Exploration**	5.38	1.16	5.71	1.10	5.66	1.08	GAIN
Average motive sum (AM)***	4.05	0.92	4.50	0.90	4.33	0.85	
Average GAIN sum (AG)***	4.53	0.88	4.78	0.91	4.70	0.81	

A one-way analysis of variance comparison of average motive sum variables (the AM variable in Table 3) between the three clusters revealed that participants of Cluster 2 were more motivated to play than those of Cluster 3 ( $p=0.0071$ , Cohen's  $d=0.20$ , 95% CI: 0.05-0.34) and Cluster 1 ( $p=0.0000$ , Cohen's  $d=0.50$ , 95% CI: 0.33-0.66). With the exceptions of *Addiction* and *Boredom*, there were statistically significant differences in all motive factors between the clusters. For Cluster 1 and Cluster 2 the effect sizes between the means were most notable in *Social* (Cohen's  $d=0.60$ , 95% CI: 0.43-0.76), *Immersive Agency* (Cohen's  $d=0.48$ , 95% CI: 0.32-0.64), *Utility* (Cohen's  $d=0.37$ , 95% CI: 0.21-0.54), and *Nostalgia* (Cohen's  $d=0.36$ , 95% CI: 0.20-0.52) motives in which Cluster 2 had clearly higher mean values than Cluster 1. Cluster 2 and Cluster 3 were relatively similar to each other regarding their motive means. Yet the Welch t-test (one-sided) found statistically significant differences between these two clusters in *Social* ( $p=0.0000$ , Cohen's  $d=0.33$ , 95% CI: 0.18-0.47), *Immersive Agency* ( $p=0.0047$ , Cohen's  $d=0.21$ , 95% CI: 0.06-0.35), *Affective Engagement* ( $p=0.033$ , Cohen's  $d=0.15$ , 95% CI: 0.01-0.30), and *Escapism* ( $p=0.027$ , Cohen's  $d=0.16$ , 95% CI: 0.02-0.30) motives. In all of these cases, the mean values of Cluster 2 were higher than those of Cluster 3.

As for the five types of gameplay activity preferences, only *Aggression* and *Exploration* sums differed between the clusters. Cluster 1 had lower *Aggression* preference than both Cluster 2 (Cohen's  $d=0.32$ , 95% CI: 0.16-0.49) and Cluster 3 (Cohen's  $d=0.18$ , 95% CI: 0.05-0.32). The same was true for the *Exploration* sum between Cluster 1 and Cluster 2 (Cohen's  $d=0.29$ , 95% CI: 0.13-0.45) and Cluster 1 and Cluster 3 (Cohen's  $d=0.25$ , 95% CI: 0.12-0.39).

## 5. Discussion and conclusions

The outcomes of informal learning in this study are based on our analysis of players' own perceptions of learning from games. We identified 11 main categories of learning outcomes. To identify potential learner types we conducted a cluster analysis. Together with comparisons between these three learner types (*Learning perseverance*, *Learning practices and communalities*, and *Learning to perform*) it revealed that players do differ from each other in what they perceive and articulate they have learned by playing games of their choice. The first notable result of the clustering process was that it clearly suggested a three-cluster solution. Each of the three clusters denoted different profiles of learning, respectively emphasising the specific areas of self-development, improving communal practices, and improving performative abilities in terms of both cognitive and behavioural skills. It is tempting to reflect on this result from the perspective of self-determination theory (Ryan and Deci, 2000), especially in terms of the three basic needs that constitute positive growth and motivation of individuals. Thus, it seems possible to make obvious linkages between the needs of Autonomy, Relatedness, and Competence, and the respective clusters of *Learning perseverance* (supporting autonomic self-development), *Learning practices and communalities* (supporting social relatedness), and *Learning to perform* (supporting the development of competence). This kind of interpretation would, however, require future studies focusing particularly on the prospect of this promising observation.

Secondly, the three learner types did have distinctive profiles, not only regarding the experienced learning outcomes but also player motives and preferred gameplay activity types. The main result of these comparisons was that the *Learning perseverance* type of player-learners were notably less motivated to play games than the other two learner types, yet they enjoyed gameplay activities of coordination, caretaking, and management similarly to the *Learning practices and communalities*, and the *Learning to perform* player-learners. The *Learning*

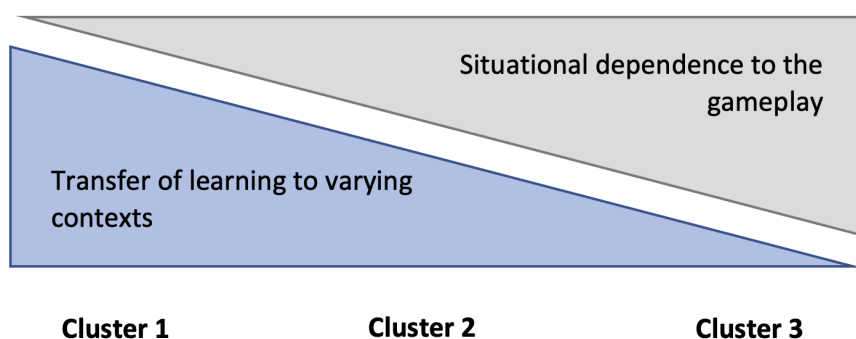


*practices and communalities* player-learners differed from the *Learning to perform* player-learners in a much more subtle way, mostly regarding the *Social* motive and the *Immersive Agency* motive.

These results indicate that playing because of social and immersive experiences is associated with a high motivation to play games and, importantly, also with learning outcomes related to interpersonal and practical skills (e.g., language skills, teamwork). Furthermore, we found that another, highly motivated player-learner type that was not as motivated by social and immersive experiences reported learning outcomes that were closely associated with performance, competence, and honing skills by overcoming game challenges. The third, less motivated learner type perhaps considers games more as a method for self-development, self-enhancement, and coping, and thus has a more instrumental relationship with game experiences than the other two learner types.

On the level of gameplay activity types, it seems that game activities that enable aggressive (e.g. shooting, killing) and explorative gameplay (e.g., character development, narrative progression) are attractive to players who (report to) have learned *practical skills*, *interpersonal skills*, *thinking skills*, and *embodied behaviours* by playing non-educational games. For the player-learners of the *Learning perseverance* type, the aggressive and explorative gameplay is not similarly attractive, which means that this learner type has more balanced gameplay preferences. Perhaps this is another indicator of them being more focused on self-development, the game and the social interactions it may enable. Related to this, it should be asked whether perceived learning and psychological need satisfaction, as argued in the SDT framework, are somehow related to each other. Our results seem to indicate that game-based learning might be closely associated with user gratification and satisfaction that players derive from games.

Given that all three learner types outlined stem from voluntary play of non-educational games, it is interesting to note how each cluster varies in terms of how dependent the learning outcomes are on gameplay (Figure 2). Most notably, the *Learning to perform* cluster seems to incorporate the closest situational dependence to the engagement with gameplay activities and “doing well” in answering the game’s challenges. This interpretation is underlined by a fact that this cluster included the largest amount of learning outcomes that were explicitly about *learning to play*. On the other end of the continuum, *Learning perseverance* cluster seems to manifest skills that are most transferable to different contexts of everyday life, while also bearing the least amount of skills with direct dependence to actual gameplay (e.g. strategizing, sensorimotor skills). The second cluster, *Learning practices and communalities*, is positioned between the other two, as it seems to both denote practical and interpersonal skills that are highly transferable while also associating with more gameplay-dependent similar skills as in the case of the third cluster.



**Figure 2:** The two-way continuums of the transfer of learning and the dependence of learning in relation to the three clusters of learning outcomes

This study demonstrated that it is possible to identify distinct informal game-based learner types based on players’ self-articulated learning outcomes. Furthermore, our analysis substantiated that these learner types are distinctive from each other also in relation to gameplay motives as well as preferences for particular gameplay activities, thus, strengthening their profiles. Further research should delve into the possible connections between informal game-based learner types and the needs outlined in self-determination theory, also because

motives to play digital games have already been extensively studied in the SDT framework (Ryan et al 2006; Przybylski et al 2010).

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