Fostering **creativity** in **learning** through digital **games**

Creative Emotional Reasoning Computational Tools Fostering Co-Creativity in Learning Processes

www.c2learn.eu

USER PROFILING AND BEHAVIOUR DETECTION

C²LEARN PROJECT DELIVERABLE NO. D3.4.3

Authors: National Centre for Scientific Research "Demokritos" (NCSR-D)

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EXECUTIVE SUMMARY

C^2Learn at a glance

C^2Learn (www.c2learn.eu) is a three-year research project supported by the European Commission through the Seventh Framework Programme (FP7), in the theme of Information and Communications Technologies (ICT) and particularly in the area of Technology-Enhanced Learning (TEL) (FP7 grant agreement no 318480). The project started on 1st November 2012 with the aim to shed new light on, and propose and test concrete ways in which our current understanding of creativity in education and creative thinking, on the one hand, and technology-enhanced learning tools and digital games, on the other hand, can be fruitfully combined to provide young learners and their teachers with innovative opportunities for creative learning. The project designs an innovative digital gaming and social networking environment incorporating diverse computational tools, the use of which can foster co-creativity in learning processes in the context of both formal and informal educational settings. The C^2Learn environment is envisioned as an open-world 'sandbox' (non-linear) virtual space enabling learners to freely explore ideas, concepts, and the shared knowledge available on the semantic web and the communities that they are part of. This innovation is co-designed, implemented and tested in systematic interaction and exchange with stakeholders following participatory design and participative evaluation principles. This happens in and around school communities covering a learner age spectrum from 10 to 18+ years.

About this document

The purpose of the present document is to describe the design and implementation of the Creativity Profiling Server (CPS) component within C2Learn. The document describes the architecture of CPS, summarizes the functionality of each integrated module and reports on the construction and maintenance of the users' creativity profile based on the creativity showcased by their creations.

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1. INTRODUCTION

1.1 USER PROFILING IN C2LEARN

Under the overall goal of fostering creativity via playful activities, C2Learn aims to incorporate technologies that monitor the creativity of the participating users, and build a Creativity-centric profile for each of them, based on their activities and the assessment creativity techniques employed during the learning process.

To this end, the initial architecture for a C2Learn profiling service, as reported in deliverable D3.4.1, aimed at providing a centralized repository for both the user's characteristics and their activities in the overall C2Learn environment, including the distinct C2Learn games and the C2Space platform. In order to improve the extensibility and reusability of the Creativity-centric profiling functionalities, and furthermore, to handle more efficiently data privacy and sensitivity issues, which importance was stressed during the 1st Project Review, several architectural changes were applied in the service.

As the provided C2Learn Games are not designed to be adaptive with respect to user characteristics, but they adapt the game progress based on the evolution of the users' creation at hand, the updated version of the C2Learn Creativity Profiling Server aims to identify patterns of creativity by analysing the produced artefacts using machine learning and data mining techniques. Towards this, it collects and processes information pertaining to all CER techniques, expressed in different modalities. More specifically, the new version of the Creativity Profiling Server is focused on storing, maintaining and analysing those constructs that strictly pertain to a user's creativity. Personal information, such as age, gender, etc., are handled by each stand-alone virtual installation of the C2Space environment. Furthermore, the data collected by the Creativity Profiling Server is completely anonymized, and the association with a specific user is known only to the calling application, as analysed in Section 3.1 of this document.

1.2 CREATIVITY PROFILING SERVER FUNDAMENTAL DESIGN PRINCIPLES

The design and implementation of the Creativity Profiling Service relies on specific concepts related to (a) the reasoning practices employed by the user and (b) the means of expressing the reasoning via artefacts of different forms.

As stated by the theoretical foundation of C2Learn, there are three core reasoning techniques related to creativity. Namely, we are concerned with the following reasoning techniques:

1. Semantic Reasoning
2. Diagrammatic Reasoning
3. Emotive Reasoning

Each of these reasoning types correspond to a creativity dimension, with specific characteristics and features. To this end, the conceptualization of the creativity profiles are based on the dimensions defined by the respective reasoning techniques.

The present deliverable describes the conceptualization of human creativity assumed by the Creativity Profiling Server and describes the server's design and implementation that serves the theoretical foundation for defining and updating a user's creativity profile. The current implementation covers the semantic dimension of creativity, as expressed via textual artefacts, while the overall architecture of the system is designed to incorporate the other dimensions of creativity.

2. CREATIVITY PROFILING SERVICES CONCEPTS

The core assumption for building a user's creativity profile, is that his/her creativity is showcased by his/her creations, named Creativity Exhibits. These exhibits can follow different modalities, corresponding to the aforementioned reasoning patterns, e.g. texts, diagrams/pictures, actions etc.

The type of creativity exhibits that CPS can handle are divided into three categories:

1. Semantic Reasoning Exhibits (SRE): This category concerns textual exhibits, such as stories.
2. Diagrammatic Reasoning Exhibits (DRE): This category concerns diagrams and image creations as exhibits
3. Emotive Reasoning Exhibits (ERE): This category concerns the behavioural actions of a user and will be further analysed in the next version of CPS (Deliverable D3.4.3).

The calculation of a creativity profile, therefore, constitutes the process of (a) measuring the creativity expressed by given creativity exhibits; (b) associating these measurements with dimensions of human creativity corresponding to the given dimension.

For achieving (a), we employ creativity metrics derived from computational creativity and formulate them in accordance to the characteristics of the examined exhibits.

A number of different creativity metrics are proposed from the literature on computational creativity [1]. More specifically, ***Novelty*** reflects the deviation from existing knowledge/ experience and can be measured as a difference metric between what is already known and the given piece of content. Novelty is a generally accepted dimension of creativity within the area of computational creativity and an essential candidate for measuring elements of creativity within the human-created content when interacting with the machine. It has been used as a heuristic for driving the generation of novel artefacts in exploratory creativity [1] known as novelty search, an approach to open-ended evolution in artificial life [2].

Surprise is another essential characteristic which may be represented as the deviation from the expected. The higher the deviation the higher the perceived surprise. Surprise offers a temporal dimension to unexpectedness [3].

Likewise, impressive artefacts readily exhibit (ease of recognition) significant design effort and may be described via two heuristics, ***Rarity*** (rare combination of properties) and ***Recreational Effort*** (difficult to achieve) [4].

These four metrics will be used to construct the creativity profile of a human user, as expressed by the artefacts that this user has been constructed alone or as a participating member of a group of users. In the case of Semantic Reasoning Exhibits, examples of such artefacts include a written story, a dialogue and any other textual creation. The present document presents the proposed model for defining human creativity aspects based on these textual artefacts (section 5).

The following section describes the overall architecture of the Creativity Profiling Server, defining the way that the creativity exhibits are propagated and processed by the server in order to produce the Creativity Profiles of its registered users.

3. CPS ARCHITECTURE

3.1 ARCHITECTURE

Figure 1 depicts the core components of the architecture along with their interrelations. The components comprising the architecture are the following:

- *C2Space* is the overall environment serving the different distinct C2Learn Games
- The *Game Registry* is part of C2Space and contains and delivers information for the games that are available for usage in game sessions
- The *Game Session Registry* is part of C2Space and stores the information for the game sessions. It is used by the relevant games in order to determine the appropriate enrolment process and setup.
- The *C2Learn Games* are the actual games used by the game session. They are responsible for the enrolment process of the users playing the game either as group members or as single players.
- The *Creativity Profiling Server* communicates with the C2Learn Games and collects the artefacts created by the players, in order to (a) calculate the Computational Creativity Metrics for these artefacts and (b) update the user's creativity profiles.

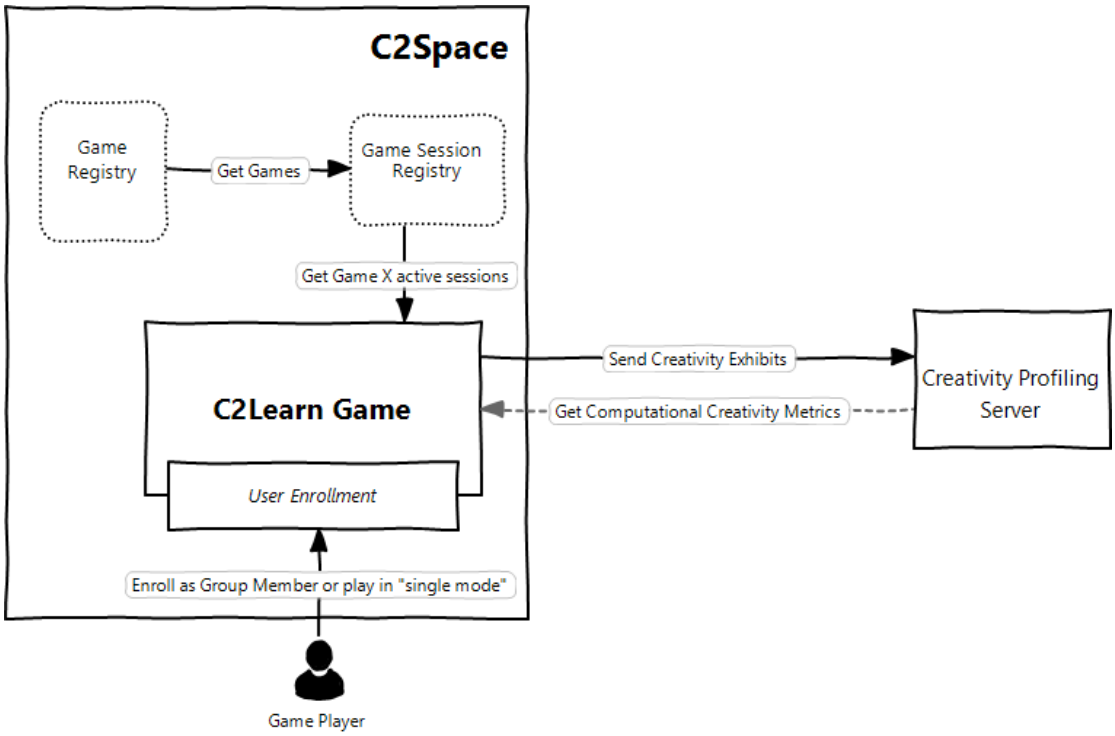

Figure 1: Overall Architecture

Consequently, the role of the Creativity Profiling Server (CPS) is to allow the storage, maintenance and update of creativity profiles of users using creativity exhibits that are produced from applications of the outside world. CPS provides a simple and straightforward API in order to expose its functionalities and to facilitate the communication with the outside world.

The following figure depicts an exemplary application inspired from C2Learn project. Through the CPS API, the example application can submit creativity exhibits and receive the corresponding creativity measurements, create group of users and finally receive the creativity profile of a user.

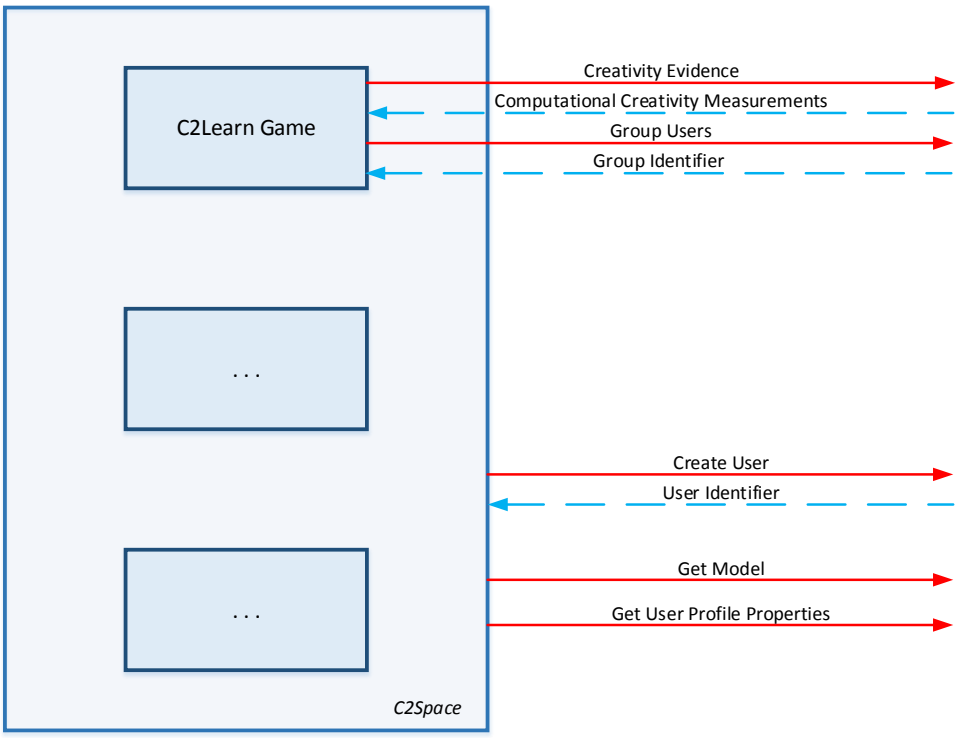

Figure 2: Example of a Client Application Communicating with CPS

The aforementioned functionalities and the internal structure of CPS are depicted to the following figure.

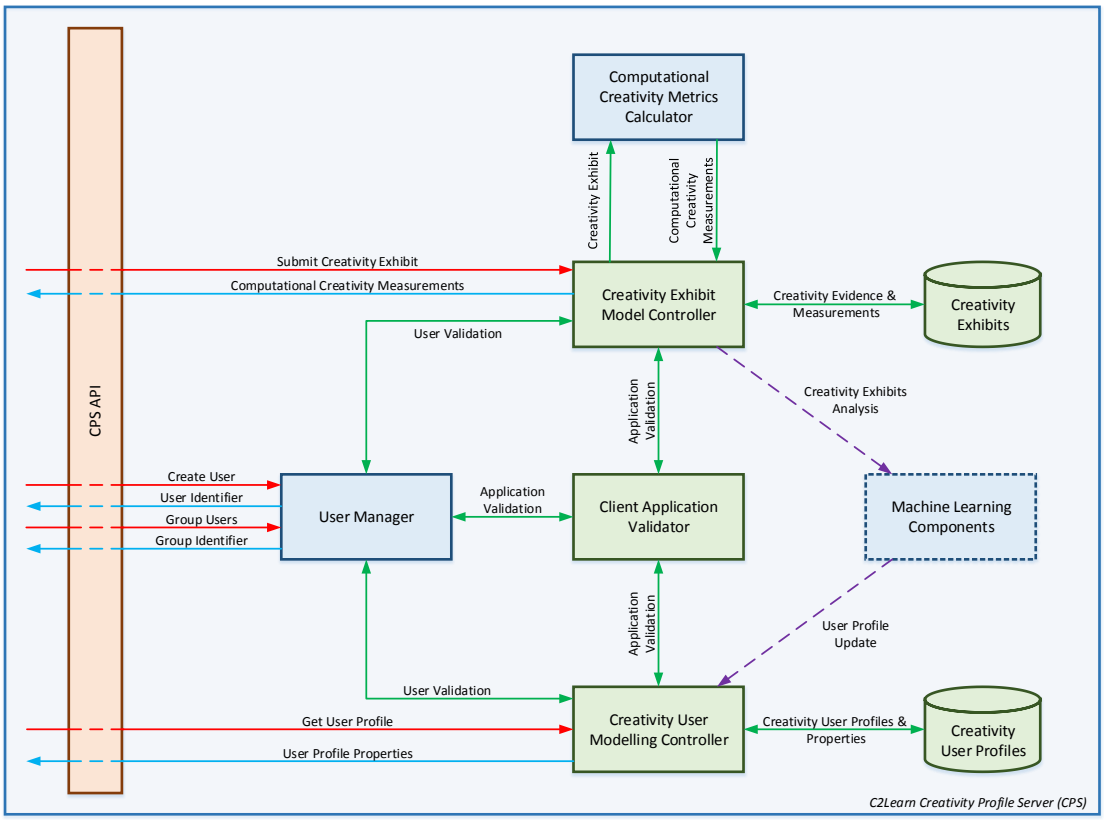

Figure 3: CPS Architecture

3.2 CPS COMPONENTS

The following table summarizes the distinct modules incorporated in the CPS architecture

CPS Module Description			
Name	**Role**	**Input**	**Output**
Client Application Validator	This module is responsible for ensuring that a client request is originated from an application registered to CPS	Application Key	Valid/ Not Valid
User Manager	This module is responsible for ensuring that client requests contain a valid user profile ID. Also User Manager is responsible for creating and destroying groups by joining and disjoining user profile properties respectively. The IDs used are completely anonymous and internal to the CPS. The association with a specific user is known only to the calling virtual installation of C2Space	User Profile ID User Profile ID List	Valid/ Not Valid Group ID
Creativity Exhibit Model Controller	This module is responsible for storing, maintaining and updating the creativity exhibits delivered by applications and also forward the creativity exhibits to the Computational Creativity Metrics Calculator.	Creativity Exhibit	Creativity Exhibit & Computational Creativity Measurements
Computational Creativity Metrics Calculator	This module is responsible for calculating all the metrics of an creativity exhibit regarding of its type	Creativity Exhibit	Computational Creativity Measurements
Creativity User Modelling Controller	This module is responsible for storing, maintaining and updating the Profile Properties of each User Profile in CPS. Also this module delivers to client applications the properties of particular user profiles.	User Profile ID Creativity Exhibits	User Profile Properties
Machine Learning Components	This module is responsible for calculating the value of the Creativity Profile Properties of a given user	User Profile ID Creativity Exhibits	User Creativity Profiles Properties

Table 1: CPS Components

3.3 CPS WORKFLOW

In a typical situation an application creates a user through the CPS API. The CPS API send the request to the User Management. Afterward User Management verifies through the Application Validation module that the application is registered to CPS. Since the application is validated User Management creates a unique user profile id and sends it to the application.

Since a user profile is created then the application can submit creativity exhibits of this user. More specifically the application submits the creativity exhibit to the CPS API along with type of the creativity exhibit and the timestamp the creativity exhibit was created.

After submission the API sends the creativity exhibit and its type to the Creativity Exhibit Model Controller module. After validating the user and the application through the User Management and the Application Validator respectively, the module sends the creativity exhibit to the Computational Creativity Metrics Calculator module.

The Computational Creativity Metrics Calculator returns back the measurements of the creativity exhibit.

Afterwards, the Creativity Exhibit Model Controller module stores the creativity exhibit along with the measurements to the CPS database.

Finally, the Creativity Exhibit Model Controller invokes the Machine Learning Components. Machine Learning Components take as input the creativity exhibit and calculate the values of the profile properties of the user. Afterwards the newly calculated values are send to the Creativity User Modelling Controller module, which stores the values to the CPS database.

Once a user creativity profile is created, then the application can request through the CPS API the User Profile Properties and also the Model which describes the profile. After sending the request to the API, the request is redirected to the Creativity User Modelling Controller module. This module, after validating the user and the application through the User Management and the Application Validator respectively, retrieves from the CPS database the properties for the corresponding user and send them back to the application.

Another functionality that an application can exploit through the CPS API, is the creation of groups. In this case the application send the user profile id that are to be grouped and the API send the request to the User Manager module. After validating the users and the application through the User Management and the Application Validator respectively, the module creates the group profile along with a unique id and returns it to the application.

4. CALCULATION OF COMPUTATIONAL CREATIVITY METRICS

This section describes the formulization of the aforementioned four Computational Creativity metrics for Semantic Reasoning Exhibits (cf. Section 2) in each of the three languages supported by C2Learn (*English, German, and Greek*), as implemented in the Computational Creativity Metrics Calculator component of the CPS.

4.1.1 NOVELTY COMPUTATION

In the context of textual information, novelty can be defined as the average semantic distance between the dominant terms included in the text, compared to the average semantic distance of the dominant terms in all texts. For the implementation of the Novelty Computation tool, we use the thirty most

frequent terms in each segment (after the removal of stopwords and the stemming of the remaining terms) as the set of dominant terms. More formally, let S_G be the set of examined texts created by the group G, T the set of dominant terms in the text belonging to G and T_n the set of dominant terms in a text segment S_n. The average semantic distance for S_n is defined as:

$$D(S_n) = \frac{\sum_{i,j=1}^{|T_n|} sem(T_{ni}, T_{nj}), i \neq j}{|T_n|}$$

Similarly, the average semantic distance for the complete set of text segments is defined as:

$$D(S_G) = \frac{\sum_{i,j=1}^{|T_G|} sem(T_i, T_j), i \neq j}{|T_G|}$$

Given this, the Novelty of a text segment S_n is equal to the absolute difference between its average semantic distance and the overall semantic distance, normalized to the [0,2] value space.

$$Nov(S_n) = 2|D(S_n) - D(S_G)|$$

4.1.2 SURPRISE COMPUTATION

As stated, surprise has a strong temporal dimension, as the surprise element largely depends on the departure from an already established context. To this end, the *Surprise Computation* service operates on a fragment set produced by a text segment. We conceptualize surprise as the average semantic distances between the consecutive fragments within this fragment set, normalized in the [0, 2] space.

$$Sur(S_n) = \frac{2}{|F| - 1} \sum_{i=2}^{|F|} |D(F_i) - D(F_{i-1})|$$

where F is the set of fragments $F_i, i \in \{1, .., , |F|\}$ of the complete text segment Sn.

4.1.3 IMPRESSIVENESS COMPUTATION

As stated, Impressiveness is in general dependent on two distinct characteristics of an artefact; its rarity, i.e. how infrequent is the artefact with respect to specific characteristics that it exhibits; and its recreation effort, i.e. how difficult it is to reproduce the artefact. We handle these two characteristics independently, as two aspects of impressiveness modelled as follows:

<u>*Rarity*</u>: We use the clustering methods implemented in the Text Clustering tool in order to compute the clusters of terms in the input text. Following the same approach applied to the computation of the novelty metric, we calculate the semantic distance between the individual clusters. In order to provide an estimation of the rarity for a given text, we calculate the sum of weights on the min-weight closure of the cluster graph compared to the maximum sum of weights in the text set of the group and normalized it in the [0, 2] space.

$$Rar(S_n) = 2\frac{MinClosureW(S_n)}{\max(MinClosureW(S_i))}, i \in \{1, .., |S_G|\}$$

where $MinClosureW(S)$ is the sum of weights in the min-weight closure of the term graph representing artefact S.

<u>*Recreation effort*</u>: Recreation effort is calculated as the number of different clusters that each text contains, compared to the maximum number of clusters found in a text segment and normalized in the [0, 2] space.

$$Eff(S_n) = 2\frac{|Clusters_n|}{\max(|Clusters_i|)}, i \in \{1, \dots, |S_G|\}$$

5. COMPUTATION OF HUMAN CREATIVITY DIMENSIONS

5.1 CORRELATION OF COMPUTATIONAL CREATIVITY METRICS WITH THE HUMAN PERCEPTION OF CREATIVITY

In order to assess the adherence of the proposed metric formulization with the human perception for creativity, we organized and conducted an experimental session based on storytelling activities. For the execution of the experiment, we employed forty (40) human participants, split in ten (10) teams of four (4) members each. All teams were asked to construct a story, on a specified premise, the survival of a village's habitants under a ravaging snow storm. The stories were created incrementally, with twenty (20) fragments produced for each story.

Following the completion of the stories, the teams were organized in two groups, each consisting of five teams. Without any interaction between the groups, each team was called to rate the stories of the remaining four teams belonging to their group, using a rank-based 4-star scale (i.e. the best story received 4 stars, the second-best story received 3 stars etc.). In this way, we obtained a ranked list of the five stories in each group. The goal of our experiment was to determine if, using the ranked lists of one of the test groups and a formalized representation of the computational creativity metrics, we can identify their correlation and examine if the distribution of values for the metrics follow the pattern of human judgment. To this end, we define a constrained optimization problem over functions of the aforementioned metrics, which is described below.

5.2 EXTRACTING A MODEL FOR THE HUMAN PERCEPTION OF CREATIVITY

Each artefact (story) S_n is characterized (via the execution of the computational creativity metrics presented in the previous section) by a set of 4 independent properties $g^{S_n} = ({g_1}^{S_n}, {g_2}^{S_n}, {g_3}^{S_n}, {g_4}^{S_n})$ where g_1 stands for "Novelty", g_2 for "Surprise", g_3 for "Rarity" and g_4 for "Recreational Effort". We define as partial creativity function (PCF) related to artefact property g_k a function that indicates how important is a specific value of the property g_k when calculating the creativity of an artefact S_n. This function is defined by the following formula:

$$PCF_{g_k}({g_k}^{S_n}) = w_{g_k} * \left(\frac{c_{g_k} * \left(1 - d_{g_k}\right)}{e^{\left(a_{g_k} * {g_k}^{S_n} + b_{g_k}\right)^2}} + \frac{d_{g_k}}{2} \right), \quad (1)$$

where ${g_k}^{S_n} \in [0,2]$is the value of property g_k for the artefact S_n, and $0 \le a_{g_k} \le 5, -4 \le b_{g_k} \le 4,\ 0 \le c_{g_k} \le 1,\ 0 \le d_{g_k} \le 2$ are parameters that define the form of the partial creativity function, whereas $0 \le w_{g_k} \le 1$ represents the weight of property g_k in the calculation of the overall creativity. The calculation of the above parameters for all g_k properties lead to the calculation of the complete creativity function (CCF), as the aggregation of the partial creativity functions, as follows:

$$CCF(g^{S_n}) = \frac{1}{4} * \sum_{k=1}^{4} PCF_{g_k}({g_k}^{S_n})$$

If CCF_{S_1} is the complete creativity of an artefact S_1 and CCF_{S_2} is the complete creativity of an artefact S_2, then the following properties generally hold for the complete creativity function:

$$CCF_{S_1} > CCF_{S_1} \Leftrightarrow (S_1)P(S_2),$$

$$CCF_{S_1} = CCF_{S_1} \Leftrightarrow (S_1)I(S_2),$$

where P is a strict preference relation and I is an indifference relation, as perceived by humans when evaluating the creativity of these artefacts.

Given a preference ranking of a reference set of artefacts, we define the creativity differences $\Delta = (\Delta_1, \Delta_2, \dots, \Delta_{q-1})$, where q is the number of artefacts in the reference set and $\Delta_i = CCF_{S_i} - CCF_{S_{i+1}} \geq 0$ is the creativity difference between two subsequent artefacts in the ranked set.

We then define an error parameter E for each creativity difference:

$$\Delta_i = CCF_{S_i} - CCF_{S_{i+1}} + E_i \geq 0.$$

We can then solve the following constrained optimisation problem:

$$Minimise \sum_{i=1}^{q-1} (E_i)^2 \text{ s.t. } \begin{cases} \Delta_i \geq 0, if\ (S_i)P(S_{i+1}) \\ \Delta_i = 0, if\ (S_i)I(S_{i+1}) \end{cases}$$

This optimisation problem leads to the calculation of the partial creativity function parameters for each property g_k.

Table 2 presents the values on the four creativity metrics calculated for the stories produced by each team in the two groups. Based on these values and the human assessment of the story rankings, the results of the constrained optimization problem defined in the previous section resolves in the calculation of the partial creativity parameters (a, b, c, d and w). The solution of the optimization problem is presented in tables 3 and 4 for Group A and Group B respectively.

	Story Ranks	Novelty	Surprise	Rarity	R. Effort
Group A	#1	1.440	0.900	1.575	0.854
	#2	0.325	1.700	0.800	1.629
	#3	1.530	0.125	1.700	0.557
	#4	1.405	0.575	1.800	0.211
	#5	0.055	1.600	1.275	1.309
Group B	#1	1.480	0.675	1.650	0.720
	#2	0.575	1.125	0.950	0.969
	#3	1.735	0.350	1.750	0.743
	#4	1.690	0.175	0.875	0.014
	#5	0.405	1.950	0.175	1.786

Table 2: Creativity Metrics Values for the Produced Stories

	Group A NLP Solution				
	a	b	c	d	w
Novelty	4.9932	-3.9748	1.0000	0.0000	1.0000
Surprise	3.0045	-2.5302	1.0000	0.0000	1.0000
Rarity	3.3335	-2.7751	0.9860	0.1611	0.9808
R. Effort	2.1063	-4.0000	0.9812	0.0214	0.9860

Table 3: Optimal Parameter Values for Group A

	Group B NLP Solution				
	a	b	c	d	w
Novelty	5.0000	-3.9452	0.9600	0.0000	1.0000
Surprise	2.8049	-2.5186	1.0000	0.0001	0.9955
Rarity	3.4441	-2.8270	0.9938	0.1605	0.9618
R. Effort	2.0258	-3.8250	0.9986	0.0214	0.9753

Table 4: Optimal Parameter Values for Group B

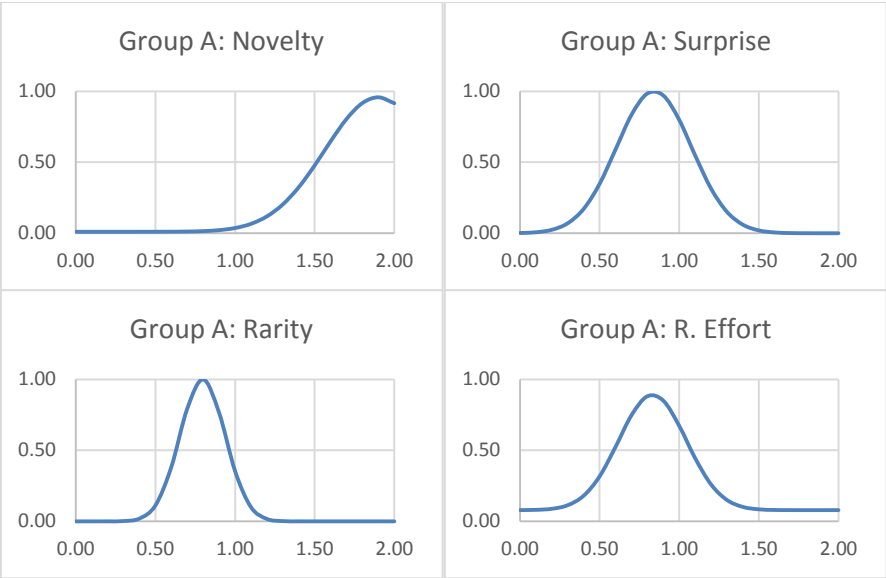

Figure 4. PCs of Computational Creativity Metrics wrt their value (Group A)

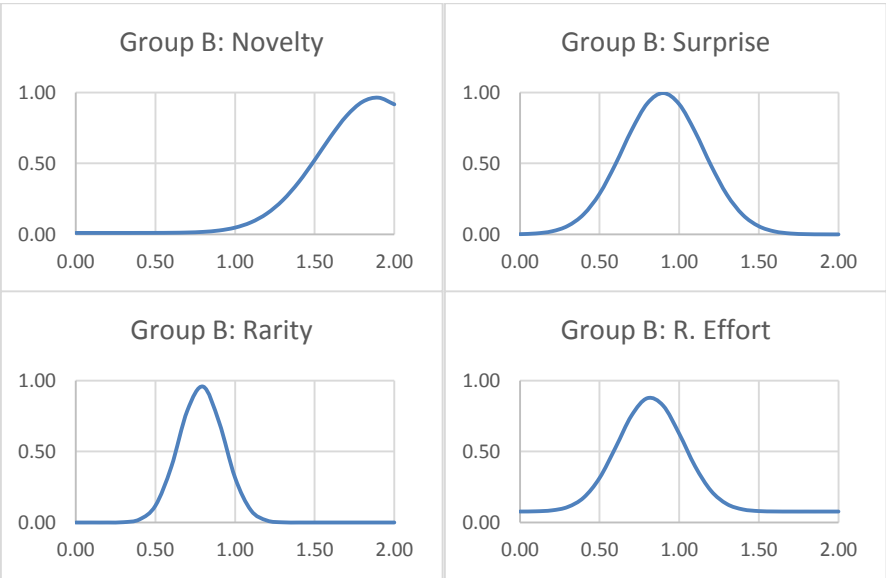

Figure 5. PCs of Computational Creativity Metrics wrt their value (Group B)

Regarding the impact of the various metrics in the computation of the overall creativity, we observed that Novelty is generally considered a particularly positive attribute creativity-wise for the stories, its partial creativity (PC) increasing as its value increases (see Figure 4). In contrast, the remaining metrics reached their maximum partial creativity at a certain value, after which their partial creativity started to decrease, indicating that e.g. recreational effort greater than a certain point is not perceived as a direct indication of creativity (see Figures 3 and 4).

Hence, the obtained results indicate that, while the proposed computational creativity metrics are correlated with the perception of humans for creativity, this correlation is not direct for all metrics. The following section discusses on the implications of these observations and details our approach for using the proposed metrics towards building a dimensional plane that more accurately reflects the human perspective for creativity.

5.3 TRANSFERRING COMPUTATIONAL CREATIVITY METRICS TO THE HUMAN PERSPECTIVE

As stated, each textual artefact can be described by 4 computational creativity metrics, namely, Novelty, Surprise, Rarity and Recreational Effort. Following the formulation of the creativity metrics, therefore, the next hypothesis that was examined was the reduction of the dimensional space for representing creativity as expressed through creative artefacts, in an orthogonal space. In order to effectively conceptualize human creativity, orthogonality is a particularly desirable attribute of the conceptualization space to be used, since it allows the examination of independent variables when trying to analyse and influence / encourage certain creativity aspects. Hence, the first step towards identifying the adherence of the computational creativity metrics with the human perspective is to examine the orthogonality of the proposed metrics formulation. To this end, we executed an experiment for calculating the four basic computational creativity metrics on two datasets derived from distinct and distant domains, and determined whether the four metrics are orthogonal.

The first dataset comprised transcriptions of European Parliament Proceedings [5]. Given the described formulation of computational creativity metrics, we consider as a "story" the proceedings of a distinct Parliament session and as a fragment the speech of an individual MP within the examined session. The second dataset was derived from a literary work, Stories from Northern Myths, by E.K. Baker, available via the Project Gutenberg collection. In this case, the story is a book chapter and the story fragment is a paragraph within the chapter.
In total, we examined 50 distinct parliament sessions from the Europarl dataset and 40 chapters from the storybook. Table 4 summarizes the acquired values for the four computational creativity metrics for a 5-item sample of the aforementioned datasets.

		Computational Creativity Metrics			
	Doc No.	**Novelty**	**Surprise**	**Rarity**	**R. Effort**
Formal Verbal Transcriptions	1	0.05090	0.15521	0.16667	0.77820
	2	0.11686	0.84821	0.25000	0.01014
	3	0.04792	0.21635	0.14394	0.56020
	4	0.07355	0.13729	0.05000	0.50697
	5	0.01267	0.12373	0.25000	0.19011
Literary Work	1	0.05138	0.10716	2.00000	1.78925
	2	0.05097	0.10142	0.26667	1.68172
	3	0.03030	0.16625	0.26667	1.60000
	4	0.06409	0.08024	2.00000	1.41075
	5	0.04940	0.14300	2.00000	1.69892

Table 5. Computational Creativity Metrics Values for Europarl and Storybook datasets

Based on the obtained results, we calculated the correlation between the four computational creativity metrics. Tables 6 and 7 provide the correlation values between the four metrics. It is evident that the computational creativity metrics by themselves are not orthogonal.

	Novelty	**Surprise**	**Rarity**	**R. Effort**
Novelty	1.00000	0.13393	0.12329	-0.40681
Surprise	0.13393	1.00000	0.26453	-0.43151
Rarity	0.12329	0.26453	1.00000	-0.33499
R. Effort	-0.40681	-0.43151	-0.33499	1.00000

Table 6. Computational Metrics Correlation: Formal Verbal Transcriptions

	Novelty	Surprise	Rarity	R. Effort
Novelty	1.00000	-0.64243	0.10392	-0.10762
Surprise	-0.64243	1.00000	0.07376	-0.02538
Rarity	0.10392	0.07376	1.00000	-0.03882
R. Effort	-0.10762	-0.02538	-0.03882	1.00000

Table 7. Computational Metrics Correlation: Literary Work

In order to better approximate the human perception for creativity, we propose the following abstraction for modelling the examined aspects of creativity to a space more closely resembling human thinking. The two dimensions of the proposed space are:

– *Novelty*, as it is a dimension that the conducted experiments showed that it has a monotonic incremental relation with the perception of humans on what is creative.
– *Atypicality*, that is, the tendency to deviate from the norm without actually breaking through.

We consider Atypicality as a combination of the Surprise, Rarity and Recreational Effort metrics, each bearing a different weight towards determining Atypicality.

These two axes also provide a rough conceptualization of the two major qualitative aspects of creative work: whether the said work is *visionary*, i.e. it provides a groundbreaking approach on a given field; and whether it is *constructive*, i.e. it uses in a novel way established techniques and ideas in order to produce a high-quality artefact.

As stated, Novelty has an analogous and close to monotonic association with the human judgment for creativity. Therefore, and in order to satisfy our requirement of orthogonality, we consider Novelty as the strictly defined dimension of our space and seek for the formulation of Atypicality that results to a dimension orthogonal to Novelty.

More specifically, let Atypicality of a text t be the normalized weighted sum of its Surprise, Rarity, and Recreational Effort:

$$A(t) = \frac{w_s Sur(t) + w_r Rar(t) + w_e Eff(t)}{w_s + w_r + w_e}, \text{ with the weights } w_s, w_r, w_e \in [-1,1].$$

We aim to find the weight values that constitute Atypicality orthogonal to Novelty for a given domain, i.e. those weight values for which Correl(Novelty, Atypicality) = 0. We thus define the following optimization problem:

$$Minimise \sum_{i=1}^{n} (\ Correl(Novelty_i,\ Atypicality_i)\ )^2 \text{ s.t. } w_s, w_r, w_e \in [-1,1],$$

where n is the number of the combined datasets.

Although the search space of the optimization problem above is highly non-linear, as it is demonstrated in the non-linear contours in Figure 5, solving this problem is straightforward. The optimum weight values in the examined case are:

$$(w_s, w_r, w_e) = (0.13951, 0.10154, 0.06905)$$

The following tables present the novelty and atypicality in the two datasets, as well as, the correlation between these two dimensions for the found optimum weight values.

The resulting model defines two orthogonal axes, Novelty and Atypicality, which define the space for measuring and characterizing the observed creativity, as an Euclidean vector, the length of which indicates the quantitative aspect of the creativity exhibited by the artefact, while its direction indicates the tendency for either Novelty (visionary creativity) or Atypicality (constructive creativity).

		Creativity Dimensions	
	Doc No.	**Novelty**	**Atypicality**
Fomal Verbal Transcriptions	1	0.05090	0.29769
	2	0.11686	0.46572
	3	0.04792	0.26921
	4	0.07355	0.19103
	5	0.01267	0.17986
Literary Work	1	0.05138	1.10149
	2	0.05097	0.50742
	3	0.03030	0.51839
	4	0.06409	1.00510
	5	0.04940	1.09751

Table 8. Creativity Dimensions Values for Europarl and Storybook datasets

	Novelty	**Atypicality**
Novelty	1.00000	2.986E-07
Atypicality	2.986E-07	1.00000

Table 9. Correlation of Creativity Dimensions: Formal Verbal Transcription

	Novelty	**Atypicality**
Novelty	1.00000	1.436E-07
Atypicality	1.436E-07	1.00000

Table 10. Correlation of Creativity Dimensions: Literary Work

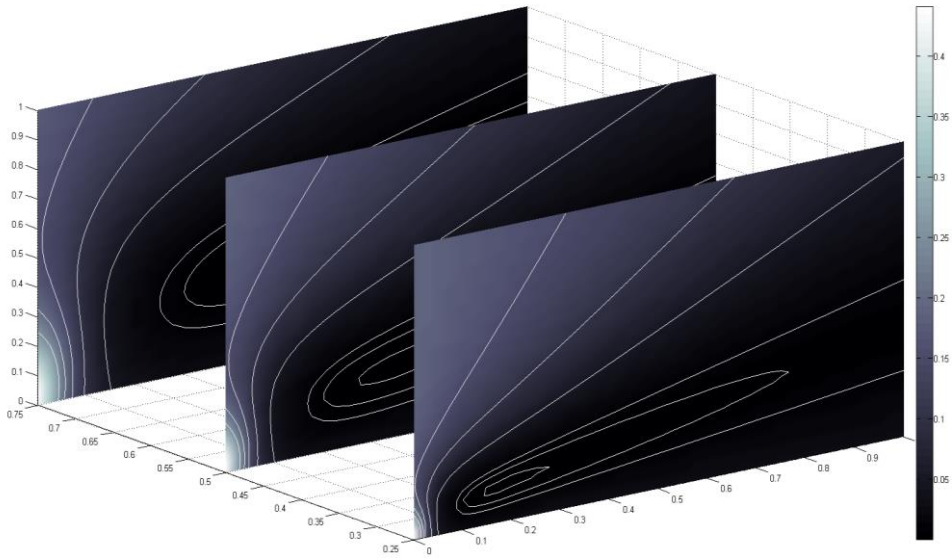

Figure 6. Non-linear Search Space: Surprise plane

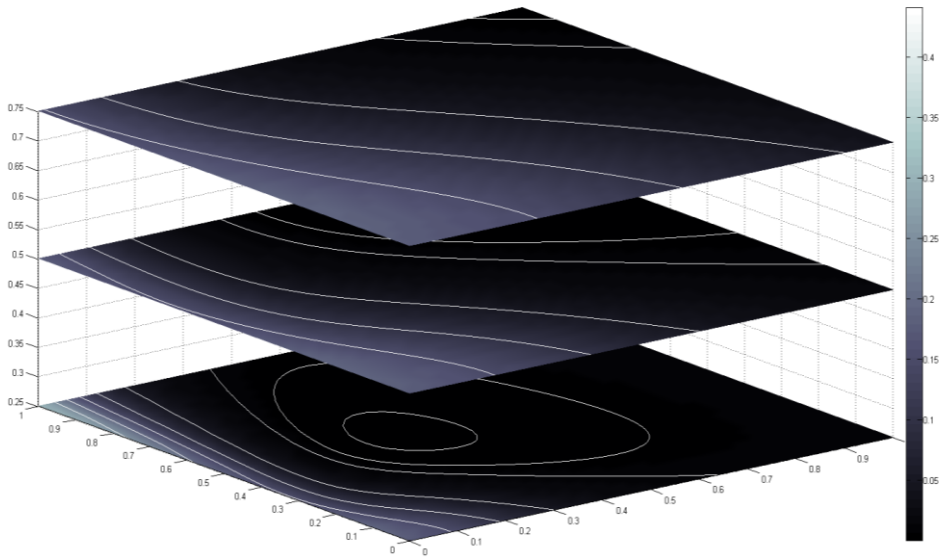

Figure 7. Non-linear Search Space: R. Effort plane

Using this model for the evaluation of the storyset of the initial experiment described in Section 5.2, and taking into account the vector length for each story, we obtained the same ranking as the one produced by the human evaluation. This is a strong indication that the proposed model accurately reflects human judgement, while also pertaining to core principles of the human perception of creativity.

5.4 INCORPORATION OF THE MODEL IN CPS

Based on the previously described experiments, we combine within CPS the Surprise, Rarity and Recreational Effort metrics in order to form another metric, which we call Atypicality and is orthogonal to Novelty. Atypicality is calculated as a weighted average of Surprise, Rarity and Recreational Effort, as follows:

$$AT_i = \frac{w_S * S_i + w_R * R_i + w_E * E_i}{w_S + w_R + w_E} \qquad [2]$$

Where:

i refers to an artifact, Si , Ri ,Ei and ATi to Surprise, Rarity, Recreational Effort and Atypicality metrics respectively for the given artifact i, and wS,wR and wE are positive weights assigned to Surprise, Rarity and Effort respectively, in order to calculate the Atypicality metric in a way as much uncorrelated (and thus, orthogonal) with Novelty as possible.

A user's Creativity Profile, thus, consists of a two-dimensional vector expressing two types of user's creativity. The Visionary Creativity, which is measured by the Novelty metric, and the Constructive Creativity, which is measured by the Atypicality metric.

CPS gathers all Creativity Exhibits (artefacts) that are produced by its users within external applications. In discrete time intervals, which we call Time Window, CPS calculates and/or updates the Creativity Profile of each user.

The calculation of the creativity profiles for the users of the CPS is a repeated (once per Time Window) two-phase process, and is explained below:

Phase A: Calculation of optimum Computational Creativity Metric Weights for the Application Domain

We aim to find/ update the weight values [wS,wR,wE] of Surprise, Rarity and Recreational Effort that constitute Atypicality orthogonal to Novelty, i.e. those weight values for which Correl(N, AT) = 0.

The optimum vector [wS,wR,wE] will be used in Phase B for the calculation of the users' Creativity Profiles for the new CPS Time Window.

We thus define the following non-linear optimization problem:

$$Min.\ Correl(N, AT)^2 \qquad \text{[Eq.2]}$$

$$st.$$

$$w_S, w_R, w_E \geq 0$$

$$w_S + w_R + w_E \neq 0$$

Each time where a new CPS Time Window starts, we solve the above minimization problem for all the artefacts of the application domain (all the creativity exhibits collected for all CPS users and for all CPS Time Windows so far).

It is evident that in each execution of this process there is a strong probability of discovering a new vector [wS,wR,wE] that makes Atypicality (AT) more orthogonal to Novelty (N). In order to reduce the sensitivity of the system to this continuous change, we update the vector [wS,wR,wE] to be used in Phase B with the new vector retrieved by solving the optimization problem defined in Eq.2 only when the improvement (minimization) in Correl(N, AT)2 exceeds 5%.

Phase B: Construct/update of Users' Creativity Profiles

A user's creativity profile is determined by the creativity exhibits produced by the user alone or as a member of a group.

Groups are treated by CPS as a user, meaning that CPS will construct a creativity profile also for each group. In this case, the creativity profile is constructed/ updated based on the creativity exhibits of the group during the last (just finished) time window.

In the case of simple users (not groups) their creativity profile is constructed/ updated based on all the creativity exhibits they constructed (either alone or as a group member).

The first step for computing the creativity profiles is to transform the space (N,S,E,R) to the space (N, AT) and compute the average of N and AT measures for the creativity exhibits for a given user and for the time window that just finished, as follows:

B1. Calculate Average Novelty and Atypicality of Creativity Exhibits

In the general case, let a user U which participates in groups UG.

In the case of computing the creativity profile of a group, we have only the user U, which represents the group. Such a user cannot be part of other groups.

Let $E_T \equiv [\overline{Novelty}, \overline{Atypicality}]$ of a user U, calculated for the creativity exhibits in the time window T, after the transformation of the space (N,S,E,R) to the space (N, AT) using the optimal weight vector [wS,wR,wE] (calculated in Phase A).

Let also $G_T \equiv [\overline{Novelty}, \overline{Atypicality}]$ of a user U, calculated for the creativity exhibits of UG in the time window T, after the transformation of the space (N,S,E,R) to the space (N, AT) using the optimal weight vector [wS,wR,wE] (calculated in Phase A).

The overall Average Novelty and Atypicality (PT) of all creativity exhibits for user U is calculated as a fusion of ET and GT, relying on the analogy of the user's and the groups' achievements.

If the user's creativity (ET) surpasses the creativity exhibited within his/her participation in groups (GT), then only ET is considered. Otherwise, a part of the difference between groups' creativity and user's creativity is also considered, as follows:

$$P_T = \begin{cases} E_T & E_T \geq G_T \\ E_T + k * (G_T - E_T) & E_T < G_T \end{cases} \quad \text{[Eq.3]}$$

where:

$$k = \frac{1}{2} + \frac{1}{2} * tanh(2 * [(G_T - E_T) - 1]) \quad \text{[Eq.4]}$$

B2. Calculate Visionary and Constructive Creativity of User

Though all exhibits must be taken into account, the recent ones are considered more important, as they depict the exact current status of the user's creativity whereas past exhibits play a less vital role. To give our model an essence of decay through time, we use this formula:

$$C_T = \frac{P_T}{D} + \frac{D-1}{D} * C_{T-1} \quad \text{[Eq.5]}$$

Where:

C_T is the vector describing the Creativity of the user (or group) at the time window T, and C_{T-1} at the time window T-1 respectively

$$C_T \equiv [Visionary\ Creativity, Constructive\ Creativity]$$

and D, a proportional constant of decaying analogous to the timespan.

6. CPS API FUNCTIONALITIES

The CPS API provides a set REST services. These services allow the communication with CPS and use its profiling capabilities. A test bed for trying the services and examining their output has been set up, based on the Swagger platform. The testing environment can be accessed at:

http://cru.iit.demokritos.gr:8500/CreativityProfileServer/#!/CreativityProfileServer

6.1 CREATE USER PROFILE

This service creates a user profile in the context of CPS. More specifically, it creates a user profile with a unique id and assigns the user to the given application.

Parameters	
Application key	The identifier of the application.

6.2 CREATE GROUP

Creates a Group and generates a Unique Identifier for the group.

Parameters	
Application key	The identifier of the application.
Users List	A semicolon-separated list of the IDs of the users belonging to the group

6.3 SUBMIT CREATIVITY EXHIBIT

This service allows to an application to submit in CPS a creativity exhibit for a specific user (or group). In the request should be also included not only the creativity exhibit but also, the type of the creativity exhibit, the user profile id, the application key and the timestamp of the creativity exhibit.

Parameters	
Application key	The identifier of the application.
User Profile ID	The identifier of the User Profile
Creativity Exhibit	The creativity exhibit
Creativity Exhibit Type	The type of the creativity exhibit
Timestamp	The timestamp the creativity exhibit was created

6.4 GET USER CREATIVITY PROFILE

This service allow an application to request and receive the creativity profile of a user.

Parameters	
Application key	The identifier of the application.
User Profile ID	The identifier of the User Profile

6.5 SUBMIT EXHIBIT PREFERENCE LIST

Stores the list of the preferred exhibits of a user. The list is ordered from the most preferred to the least preferred.

Parameters	
Application key	The identifier of the application.
User Profile ID	The identifier of the User Profile
Exhibit List	A semicolon-separated list of exhibit IDs sorted in order of preference

6.6 SUBMIT USER INFORMAL EVALUATION LIST

Stores the rank of the creativity evaluation of users from the most creative to the least creative. If the evaluation is based on established evaluation procedures the evaluation is formal, otherwise is informal.

Parameters	
Application key	The identifier of the application.
User Profile ID	The identifier of the User Profile
Users List	A semicolon-separated list of User IDs in descending order of creativity as perceived by the specific user

6.7 SUBMIT USER FORMAL EVALUATION LIST

Stores the rank of the creativity evaluation of users from the most creative to the least creative. This service is used when the evaluation is based on established evaluation procedures, in contrast to the informal evaluation handled by the service described in section 6.6.

Parameters	
Application key	The identifier of the application.
Users List	A semicolon-separated list of User IDs in descending order of creativity as determined by the formal evaluation

7. CPS DATABASE SCHEMA

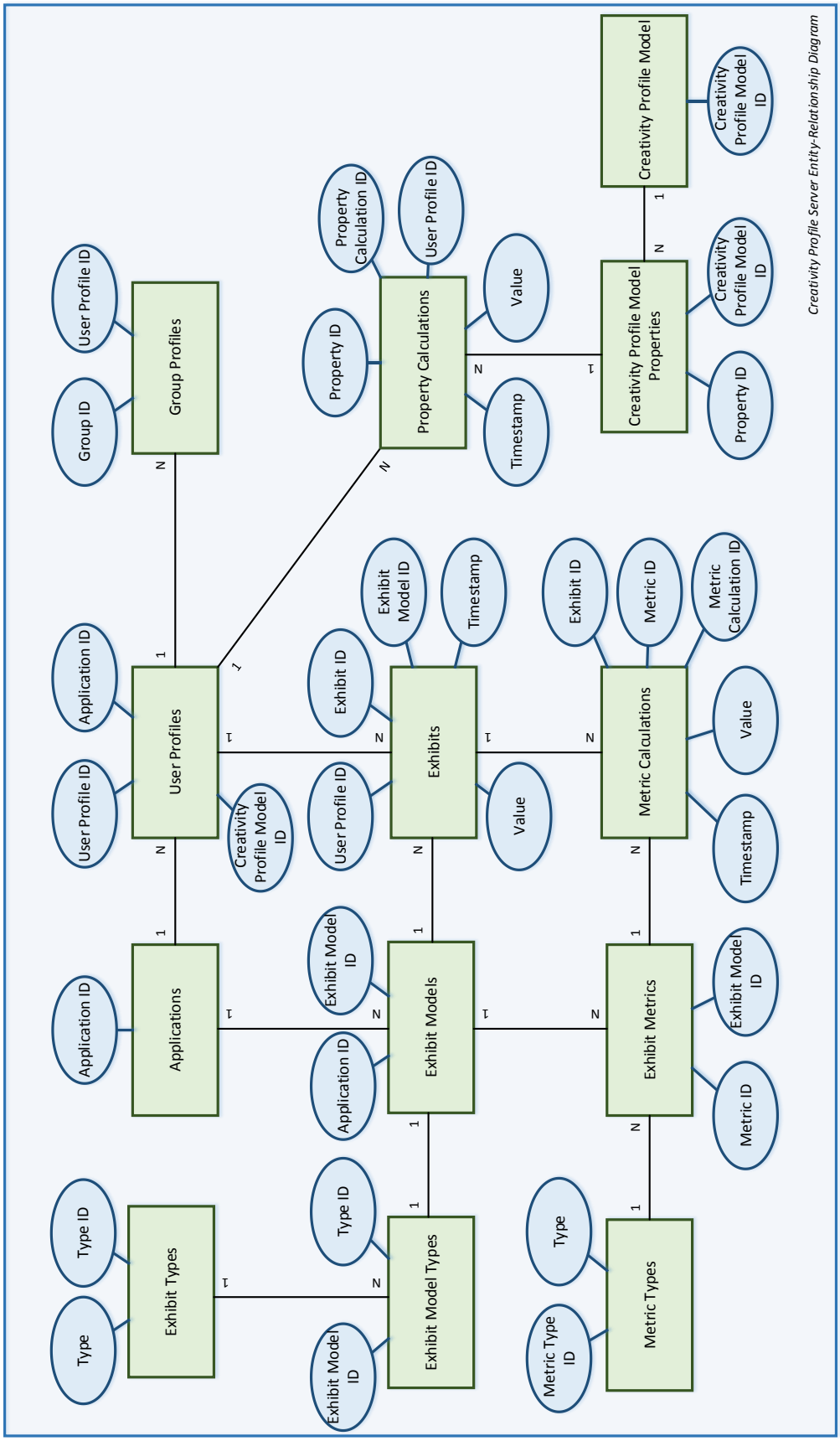

Figure 8: CPS Database Schema

8. CONCLUSIONS

The present report provides a summary of the architectural design and functionality of the C2Learn Creativity Profiling Server (CPS). The CPS aims to anonymously handle and store all the creativity exhibits created by a given user and use these exhibits to construct the latter's creativity profile following a formally defined model.

The CPS is designed to support exhibits for all three different reasoning dimensions foreseen in C2Learn. At its current implementation, the CPS handles artefacts pertaining to the Semantic Reasoning dimension, i.e. textual artefacts / exhibits. For handling Diagrammatic Reasoning Exhibits, the CPS could incorporate external services that calculate Computational Creativity Metrics over Diagrammatic exhibits, like the tools designed and developed in the context of WP4 of the C²Learn project, and more specifically T4.3, Mixed-initiative Procedural Content Generation.

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